



*FINAL REPORT*

## Issues in Urban Trip Generation

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NITC-DIS-1000 ■ August 2017

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national university transportation center.*





# **ISSUES IN URBAN TRIP GENERATION**

## **Final Report NITC-DIS-1000**

by

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**August 2017**

## Technical Report Documentation Page

1. Report No. NITC-DIS-1000	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle  Issues in Urban Trip Generation		5. Report Date August 2017	
		6. Performing Organization Code	
7. Author(s)  Kristina Marie Currans		8. Performing Organization Report No.	
9. Performing Organization Name and Address  Portland State University PO Box 751 Portland, Oregon 97201		10. Work Unit No. (TRAIS)	
		11. Contract or Grant No.	
12. Sponsoring Agency Name and Address  National Institute for Transportation and Communities (NITC) P.O. Box 751 Portland, Oregon 97207		13. Type of Report and Period Covered	
		14. Sponsoring Agency Code	
15. Supplementary Notes			
<p>16. Abstract</p> <p>In 1976, the Institute of Transportation Engineers (ITE) compiled their first Handbook of guidelines and methods for evaluating development-level transportation impacts, specifically vehicular impacts (Institute of Transportation Engineers 1976). Decades later, these methods—essentially the same as when they were originally conceived—are used ubiquitously across the US and Canada. Only recently, with the guidelines in its third edition of the ITE's Trip Generation Handbook (Institute of Transportation Engineers 2014) new data and approaches been adopted—despite substantial evidence that questions the accuracy of older data (Clifton, Currans, and Muhs 2012; Shafizadeh et al. 2012; Weinberger et al. 2015), automobile bias (Clifton et al. 2012; Millard-Ball 2015; Manville 2017), and lack of sensitivity to urban contexts (Currans and Clifton 2015; Ewing et al. 2011; Schneider, Shafizadeh, and Handy 2015; Weinberger et al. 2015).</p> <p>This dissertation contributes to this literature by focusing on the data, methods, and assumptions so commonly included in development- or site-level evaluation of transportation impacts. These methods are omnipresent in development-level review—used in transportation impact analyses or studies (TIAs/TISs) of vehicular or mode-based impacts, vehicle miles traveled (VMT) and estimates of emissions, scaling or scoping development size, and evaluating transportation system development, impact or utility fees or charges. However, few have evaluated the underlying characteristics of these foundational data—with few exceptions (Shoup 2003)—this manuscript takes aim at understanding inherent issues in the collection and application of ITE's data and methods in various urban contexts.</p> <p>This manuscript includes a compiled dissertation, four papers written consecutively. The first, evaluates state-of-the-art methods in Chapter 2—identifying gaps in the literature. Two such gaps are explored in Chapter 3 and Chapter 4. In Chapter 3, a larger implicit assumption present in ITE's methods—that the existing land-use taxonomy is an optimal and accurate way to describe land use and segment data. Results indicate a simplified taxonomy would provide substantial reductions in cost corresponding with a minor loss in the model's explanation of variance. Following, Chapter 4 explores a common assumption that requires ITE's vehicle trips be converted into person trips and applied across contexts. The results point to the need to consider demographics in site-level transportation impact analysis, particularly to estimate overall demand (person trips, transaction activity) at retail and service development.</p> <p>In Chapter 5, the findings from this research and previous studies are extrapolated to evaluate and quantify the potential bias when temporal, special, and social contexts are ignored. The results indicate the compounding overestimation of automobile demand may inflate estimation by more than 100% in contexts where ITE should be applicable (suburban areas with moderate incomes). In the conclusions (Chapter 6), the implications of this work are explored, followed by recommendations for practice and a discussion of the limitations of this research and future work.</p>			
17. Key Words  Transportation impact studies; trip generation; land use development; Institute of Transportation Engineers		18. Distribution Statement No restrictions. Copies available from NITC: <a href="http://www.nitc-utc.net">www.nitc-utc.net</a>	
19. Security Classification (of this report)  Unclassified	20. Security Classification (of this page)  Unclassified	21. No. of Pages  218	22. Price

## **ACKNOWLEDGEMENTS**

Kristina Currans would like to acknowledge partial support from the National Institute of Transportation and Communities (NITC) under grant number 1000, the Federal Highway Administration and Dwight David Eisenhower Graduate Transportation Fellowship, and the Portland State University Maseeh College of Engineering Graduate Fellowship. She would also like to acknowledge donations of data access from the Institute of Transportation Engineers and two local partners (retail chains who wish to remain anonymous).

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## **RECOMMENDED CITATION**

Currans, Kristina M. *Issues in Urban Trip Generation*. NITC-DIS-1000. Portland, OR: Transportation Research and Education Center (TREC), 2017.

## **ABSTRACT**

In the 1976, the Institute of Transportation Engineers (ITE) compiled their first *Handbook* of guidelines and methods for evaluating development-level transportation impacts, specifically vehicular impacts (Institute of Transportation Engineers 1976). Decades later, these methods—essentially the same as when they were originally conceived—are used ubiquitously across the US and Canada. Only recently, with the guidelines in its third edition of the ITE's *Trip Generation Handbook* (Institute of Transportation Engineers 2014) new data and approaches been adopted—despite substantial evidence that questions the accuracy of older data (Clifton, Currans, and Muhs 2012; Shafizadeh et al. 2012; Weinberger et al. 2015), automobile bias (Clifton et al. 2012; Millard-Ball 2015; Manville 2017), and lack of sensitivity to urban contexts (Currans and Clifton 2015; Ewing et al. 2011; Schneider, Shafizadeh, and Handy 2015; Weinberger et al. 2015).

This dissertation contributes to this literature by focusing on the data, methods, and assumptions so commonly included in development- or site-level evaluation of transportation impacts. These methods are omnipresent in development-level review—used in transportation impact analyses or studies (TIAs/TISs) of vehicular or mode-based impacts, vehicle miles traveled (VMT) and estimates of emissions, scaling or scoping development size, and evaluating transportation system development, impact or utility fees or charges. However, few have evaluated the underlying characteristics of these foundational data—with few exceptions (Shoup 2003)—this manuscript takes aim at

understanding inherent issues in the collection and application of ITE's data and methods in various urban contexts.

This manuscript includes a compiled dissertation, four papers written consecutively. The first, evaluates state-of-the-art methods in Chapter 2—identifying gaps in the literature. Two such gaps are explored in Chapter 3 and Chapter 4. In Chapter 3, a larger implicit assumption present in ITE's methods—that the existing land-use taxonomy is an optimal and accurate way to describe land use and segment data. Results indicate a simplified taxonomy would provide substantial reductions in cost corresponding with a minor loss in the model's explanation of variance. Following, Chapter 4 explores a common assumption that requires ITE's vehicle trips be converted into person trips and applied across contexts. The results point to the need to consider demographics in site-level transportation impact analysis, particularly to estimate overall demand (person trips, transaction activity) at retail and service development.

In Chapter 5, the findings from this research and previous studies are extrapolated to evaluate and quantify the potential bias when temporal, special, and social contexts are ignored. The results indicate the compounding overestimation of automobile demand may inflate estimation by more than 100% in contexts where ITE should be applicable (suburban areas with moderate incomes). In the conclusions (Chapter 6), the implications of this work are explored, followed by recommendations for practice and a discussion of the limitations of this research and future work.

## **DEDICATION**

To my many communities.

## **ACKNOWLEDGMENTS**

Where to begin.

I have been very privileged to have many people in my career who have provided unwavering support and guidance. There is no way I will be able to name them all in less than the length of the actual dissertation. So I will try (and probably fail), but the important thing to take away from this section is that this manuscript could not have been completed alone.

If I am considering the sheer impact of influence, I should start with my committee Chair Dr. Kelly J. Clifton. Kelly has provided more support, guidance, advice and grounding reminders than any advisor should be required to provide. And yes, I probably needed it all, even when I did not think so but secretly realized later that I was gloriously wrong. I hope I have soaked it all in, but I realize that the scale of her influence in my thought, my direction, and my work is likely more prominent than I will ever know. I appreciate everything you have done for me.

There were several partners in this work that provided data or assistance. The Institute of Transportation Engineers allows me access to their data via the third-party software OTISS by Transoft Solutions, who also agreed to this. Dr. Liming Wang used his prolific coding skills to help me compile the complete dataset. And although they have asked to remain anonymous, two local Portland retail chains provided transactions counts for many of their establishments, for which Chapter 4 was based on. Funding support was partially provided by the National Institute of Transportation and Communities (NITC) under grant number 1000, the D. D. Eisenhower Graduate

Transportation Fellowship under grant number DTFH6416G00057, and the Maseeh College of Engineering Graduate Fellowship.

I have also received long standing support from my committee members and faculty from the Civil Engineering and Urban Planning departments. The team at the NITC—and all the earlier iterations of this team—has provided substantial financial and emotional support, opportunities for travel and career development, and also for fun. Thank you all for your continued support of my work and of me as a person, researcher, student, and soon a faculty.

I would thank the students and staff of PSU, but I think it is more apt just to call them friends and include the impressive and wide-ranging support they provided—which includes listening ears, shoulders to cry on, funny bones to lean on, and brains to pick. In three minutes, I counted over 100 friends at Portland State that have influenced me, so here I'll name just a few. Adam, who has a knack for distracting me at the right moments and reminding me to make fun of myself—he does that well. Alex, who shares a similar excitement for (realistically mundane) aspects of data processing and analysis and whose frankness I can depend on. Chris, whose ability and skill to communicate information comes into my mind every time I make a graphic (and for most of my work, I still see him pinching his lips with a *hmm, let's think about this*). Sara, who reminds me that there is always someone busier than myself (and it is usually her). Eric, who reminds me that it is never too late to rethink your approach, no matter the topic or task, and (rule one) bring a towel. Amanda, for bringing herself to the table when I could not envision getting anything else but this manuscript done, and then crushing it. Joe, Steve, and Patrick, for

being people I could count on for many things, most importantly (a) happy hour, and (b) good conversation. Sirisha and Courtney, for being the dependable ears and steadfast friends. Selam, who is what I hope to be in a teacher—hilarious, witty, bright, and hard-working (in no particular order). Kelsey and Marilou, obvi. Mandy, for helping me set goals that have nothing to do with page or word counts, and for giving me the tools to destroy them. Ariel, who is perhaps the most insightful friend I have ever met and is the person who gets nearly every joke I ever tell (you cannot win them all) and laughs as hard as I do. Kelly, who I have already thanked, but who has provided so much in friendship and support; thanking her again does not even begin to do it service. To all the people who bought me a beer, who listened to me complain, who listened to me tell a story that went nowhere, who laughed with me or at me, who critiqued me. Those who let me travel with them, fail at shuttle board with them, organize social hours and gingerbread events with them. And then those Kattarshians, who I can hardly keep up with, but who kept me calm through the final months.

For the TPAU group (Bill, Alex, Becky, Megan and the whole crew), who provide both opportunity of experience and sparked my interest in this field from the beginning. And for all the people I have worked with and interacted with along this long education highway, it is hard to know where I would be without you. You all have shaped what I now realize I need, nay, require in a work place—a fun, social, non-work work crew with brains, bronze, and brilliantly beautiful personalities. From you, I have #workcrewgoals.

The true unsung heroes of this work are not affiliated with this work at all, but instead have provided me with continued and unconditional support as a family, extended family, and friend-family. First and foremost my parents, who have always provided a safety net that, even when I was not able to realize it, allowed me to take risks that I may not have even considered without them. Dad, for the fraction of his intensity—and love of anything with moving parts—that I inherited; you are the reason I cannot stop spending money on Kickstarter’s technology page. Mom, as a woman pioneering the way through the sciences, you are the reason why I—as so many other women—was able to participate in my education to the degree that I did, and also to graduate. Also, without you I would have probably never understood algebra (Dad certainly was not helping). And as my first editor, you were the first one to tell me my writing lacked organization or sense; I cannot write “in order to” without thinking about deleting “in order”. But I am fortunate for having an enormous family (in numbers not necessarily weight). So there are many more people to thank for their support. This includes, but is not limited to: Mom, Dad, Grandpa and Grandma Niehuser, Grandpa and Grandma Currans, Kate, Pat, Kelly, Carl, Katie, Thor, Biscuit, and all my aunts, uncles and cousins on both sides. Special shout out to Kelsey, who is a fantastic fellow animal lover and who reminds me that awkwardness is a virtue. And, as of the day before my defense, I can also include all the new relatives and friends that I recently gained in what I think was a deal heavily biased in my favor. I am very privileged to have so many supportive family members.

Implied, but not explicit yet: I want to acknowledge Cody. His patience with me is impressive and broad. If anyone can talk me off a "failure" cliff, it is him. And with heavy sarcasm.

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## CHAPTER 1 INTRODUCTION

In 1976, the Institute of Transportation Engineers (ITE) compiled their first *Handbook* of guidelines and methods for evaluating development-level transportation impacts, specifically vehicular impacts (Institute of Transportation Engineers 1976). With the growing expansion of suburban development, the purpose of this report was to provide practitioners with an off-the-shelf evidentiary database for understanding and evaluating vehicular impacts. Engineers and planners use this information to estimate the effects of development, evaluate these impacts against a standardized metric regulated by the local agency (e.g., level-of-service), and recommend mitigations necessary to maintain service and share the burden of development between the agency and developer.

Decades later, these methods—essentially the same as when they were originally conceived—are used ubiquitously across the US and Canada. Only recently, with the guidelines in its third edition of the ITE's *Trip Generation Handbook* (Institute of Transportation Engineers 2014) have new data and approaches been adopted—despite substantial evidence that questions the accuracy of older data (Clifton, Currans, and Muhs 2012; Shafizadeh et al. 2012; Weinberger et al. 2015), automobile bias (Clifton et al. 2012; Millard-Ball 2015; Manville 2017), and lack of sensitivity to urban contexts (Currans and Clifton 2015; Ewing et al. 2011; Schneider, Shafizadeh, and Handy 2015; Weinberger et al. 2015). The corresponding ITE *Trip Generation Manual*, a supplement to the *Handbook*, continues to contain the nearly all the original suburban vehicle trip generation data collected since its creation (Institute of Transportation Engineers 2012).

Because one cannot be used without the other, this manuscript refers to the ITE *Trip Generation Handbook* (methods) and the *Trip Generation Manual* (data) as one in the same: the *Handbook*.

This dissertation contributes to this literature by focusing on the data, methods, and assumptions so commonly included in development- or site-level evaluation of transportation impacts. These methods are omnipresent in development-level review—used in transportation impact analyses or studies (TIAs/TISs) of vehicular or mode-based impacts, vehicle miles traveled (VMT) and estimates of emissions, scaling or scoping development size, and evaluating transportation system development, impact or utility fees or charges. Few have evaluated the underlying characteristics of these foundational data—with few exceptions (Shoup 2003)—this manuscript takes aim at understanding inherent issues in the collection and application of ITE’s data and methods in various urban contexts.

The main objective and contribution of this work is connecting practice with the deep and broad travel behavior literature. For many decades, the basic practice of development-level trip generation estimation has remained stagnant, despite a growing body of demand-estimation research. These data are primarily used to evaluate and share the transportation impacts of new development between the local agency and the developer (e.g., charges or fees incurred, transportation facility mitigations required). By investigating these data—and their corresponding bias, inaccuracies, precision, and error—through the lens of theories and prior research, I may develop a stronger

foundation and guidance for improved methods and data that lead to more accurate methods and a more fair system.

This research builds on my experiences on several research projects focusing on trip generation data and methods, including: evaluating the influences of the built environment (Clifton, Currans, and Muhs 2012; Currans 2013), exploring error in existing methods through observation (Clifton et al. 2017), incorporating innovative approaches into practice (Clifton and Currans 2015), and two on-going projects exploring the variation of trip generation at subsidized affordable housing<sup>1</sup> and new housing products (e.g., micro-apartments, zero-parking housing)<sup>2</sup>. Ideas and inspiration were also developed through the author's service panels and committees, including the ITE Expert Panel on Urban Trip Generation, Committee to revise the 3<sup>rd</sup> Edition ITE's *Handbook*, and five different project panel committees.

The remainder of this introduction provides an overview of this compilation dissertation which includes four articles, followed by a concluding chapter.

Chapter 2 describes an overview of applications of development-level transportation impact estimation, a review of the state-of-the-art methods, a critique of these methods, and an outline of the overall direction of recent studies. From this investigation, several themes were identified and defined, revealing and outlining gaps

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<sup>1</sup> Project funded by Caltrans and led by Dr. Kelly J. Clifton, Portland State University.

<sup>2</sup> Project funded by the National Institute of Transportation and Communities and led by Dr. Kelly J. Clifton, Portland State University.

that need further study. While approaches in this field are inherently trying to capture demand, few methods consider the people making the trips: demographics, access to opportunities, overall demand for activities and the corresponding behavioral patterns. Among gaps identified, there remains a heavy reliance on the ubiquitously-available *Handbook*. It is from these gaps identified that the following three chapters were derived.

Chapter 3 examines a larger implicit assumption present in ITE's methods—that the existing land-use taxonomy is an optimal and accurate way to describe land use and segment data. In this chapter, ITE's vehicle-trip rates for retail and services are explored. Two analyses were conducted to examine: (a) the relationship between the age of the data and vehicle-trip rates—an often-contested topic that has resulted in little change in practice; and (b) quantifying the contribution of ITE's land-use taxonomy to explaining of variation in trip rates. The combination of these two analyses suggest that vehicle-trip rates have declined over time—although the lack of transparency of ITE's data (e.g., location information and context) limits the ability to understand whether this was due to shifts in behavior or changes in data collection protocols. An aggregated taxonomy is developed using only the data from the previous 10 years—reducing 32 retail and service land-use categories to 3. The results indicate that segmenting retail and service land uses by three categories (heavy goods, convenience uses, and everything else) performed nearly as well as the ITE's more extensive taxonomy currently. The costs of ITE's extensive taxonomy are explored further. If a complete data set with a sample size of 10 observations were to be maintained—using the full taxonomy considered for data of all ages, 67 categories—it would cost approximately \$5.3-6.7 million US dollars in data

collection every 10 years. And this is a conservative estimate that considers only retail and service uses (a fraction of the more than 170 categories). This number does not yet account for the need to capture a wider variety of urban contexts. Recommendations for practice are explored in the discussion and conclusions.

Chapter 4 explores a major assumption applied in the use of ITE's data. Nine out of 13 of the innovative methods reviewed in Chapter 2 rely upon ITE's data as a "baseline" or foundation for estimating demand across urban contexts. This process relies on a major assumption that (converted) person-trip counts estimated for suburban contexts would apply in more urban areas. This assumption is inconsistent with theories of urban economics—most notably bid-rent theory—which recognize that businesses pay a premium to locate in areas with high levels of accessibility to attract more customers. In addition, most transportation impact analyses have ignored income effects, even though socio-economics are a proven driver of activity levels in retail locations.

In this chapter, the performance of this conversion protocol itself is explored, comparing observed and estimated (converted) person-trip rates. The results indicate substantial error in four land-use categories (office, residential, retail, and service). For retail and services, however, this error was considerably biased toward underestimating activity (person trips). Then, transaction counts for 93 grocery and convenience markets in Portland, Oregon were examined to explore the relationship between local and regional accessibility and median income levels with overall activity levels (transaction counts). In a multilevel negative binomial regression, the accessibility and income were regressed upon weekly, daily, and peak-hour transaction rates. While there was not enough

evidence to suggest a significant relationship between accessibility and transaction rates, the results did indicate a significant relationship with median income of the surrounding area. The implications point to the need to consider demographics in site-level transportation impact analysis. The conclusions also provide a discussion about the use of alternative forms of data in transportation impact analyses—such as, transaction as a proxy for person-trip rates.

Because so many of the existing methods rely on ITE's *Handbook*, Chapter 5 explores these foundational data upon which so many innovative and conventional approaches rely—the methods and data collection protocols from the ITE's *Handbook* (2014) and *Manual* (2012). In this chapter, I explore the derivation and initial context in ITE's data, to the furthest extent possible. While several previous studies question the accuracy of these data (Weinberger et al. 2015; Shafizadeh et al. 2012; Millard-Ball 2015), this chapter explores the underlying temporal, spatial, and social contexts of ITE's data. The results indicate the compounding overestimation of automobile demand may inflate estimation by 100% or more in contexts where ITE should be applicable (suburban areas with moderate incomes). A discussion about the land-use development implications of this inflation in practice is explored.

This dissertation begins by evaluating state-of-the-art methods in Chapter 2 and identifying gaps in the literature. Two such gaps are explored in Chapter 3 and Chapter 4. In Chapter 5, the findings from this research and previous studies are extrapolated to evaluate and quantify the potential bias when temporal, special, and social contexts are ignored. In the conclusions (Chapter 6), the implications of this work as a whole are

explored, followed by recommendations for practice and a discussion of the limitations of this research and future work.

Many of the ideas and concepts tested and discussed in this dissertation were identified with or by the Chair of the dissertation committee, Dr. Kelly J. Clifton.

Because of this collaborative background, contributions from both myself (Currans) and the Chair (Clifton) are quantified and described for each chapter in Table 1-1.

**Table 1-1 Author’s Contribution to Each Chapter**

Chapter	Currans	Clifton	Description
2	95%	5%	I contributed 100% to the conception, analysis, interpretation, and writing of this paper—originally written as the appendix of the dissertation proposal. However, Dr. Clifton contributed through discussion and encouraged me to develop it into a paper for publication.
3	95%	5%	I contributed 100% to conception, analysis, interpretation, and writing of this paper. However, Dr. Clifton contributed through discussion and conversation on the multiple related projects I have participated in. She also encouraged me to explore the compounding influences of the error and bias in these data—a factor I explored while working on a related project with Dr. Clifton, but had not considered incorporating into this manuscript.
4	95%	5%	While I contributed the majority of the conception of this study, Dr. Clifton contributed between 10-20%. I contributed 100% of the analysis, interpretation, and writing of this paper.
5	85%	15%	The conception of this paper—or rather the need to review this specific ubiquitous and pernicious assumption—was derived by Dr. Clifton. She also the first, to my knowledge, to association this assumption to conflicts with urban spatial structure theories (Clifton, Currans, and Muhs 2012). Perhaps a small contribution in terms of time, but large in impact. It was only later in my work with this question that I realized the potential extent of error—or more importantly, the bias—from which this chapter was formed. Because of this, I credit Dr. Clifton with approximately 50% of the conception of this paper. My 50% was spent formulating the research design, purpose, and impacts and developing the concept for the research question itself. I contributed 100% of the analysis, interpretation, and writing of this paper.

**CHAPTER 2 ISSUES IN TRIP GENERATION METHODS FOR  
TRANSPORTATION IMPACT ESTIMATION OF LAND-USE DEVELOPMENT:  
A REVIEW AND DISCUSSION OF THE STATE-OF-THE-ART APPROACHES**

First published in the *Journal of Planning Literature* (2017).

DOI: 10.1177/0885412217706505

**Introduction**

The Institute of Transportation Engineers (ITE) *Trip Generation Handbook* (Institute of Transportation Engineers 2014) and the corresponding *Manual* (Institute of Transportation Engineers 2012) are the predominant resources for estimating transportation impacts generated by new development in the United States. Over the past 15 years, a substantial amount of research has been published evaluating the ability for current state-of-the-practice methods, namely ITE’s *Trip Generation Handbook*, to more accurately predict multimodal traffic impacts in urban areas, such as (Bochner et al. 2011; Clifton, Currans, and Muhs 2013; Daisa and Parker 2009). While the *Handbook* has remained a resource of “guidance” (Institute of Transportation Engineers 2014)—recommending analysts collect their own data where the context of the site does not reflect typical ITE locations: suburban, single-use, vehicle-oriented development with unconstrained parking—but constrained budgets for both agencies and practitioners have caused a call for more urban data and methods (Bochner et al. 2016). In response, the most recent edition of the *Handbook* (Institute of Transportation Engineers 2014) has begun to incorporate the vast number of studies aimed at improving the collection of multimodal data and the estimation of multimodal impacts at new developments in urban

areas, such as (Clifton, Currans, and Muhs 2015; Shafizadeh et al. 2012; Ewing et al. 2011; Daisa et al. 2013). However, the existing state-of-the-art methods do not control for a number of important aspects, that are outlined in our manuscript.

While others have evaluated the error in prediction of these methods (Sandag 2010; Shafizadeh et al. 2012; Millard-Ball 2015; Shoup 2003), discussion about evolving data collection for urban, multimodal contexts (Clifton, Currans, and Muhs 2013; Schneider, Shafizadeh, and Handy 2015; Weinberger et al. 2015), and how these methods are implemented in practice (Bochner et al. 2011; Clifton, Currans, and Muhs 2012), the focus of this manuscript is aimed at reviewing these methods and others for consistency with theories of travel behavior and urban economics, of which the literature is both far reaching and plentiful, but rarely framed around transportation impact analyses.

To identify methods, multiple Google Scholar and library searches were used to identify a list of studies and methods aimed at improving trip generation estimation for transportation impact analyses (TIA) or studies (TIS). Phrases including “trip generation” and “transportation/traffic impacts analysis/studies” were used to identify a first cut list of methods. Methods that were not (a) developed using data collected in the United States (US) (b) within the past 15 years and (c) published within a peer review process (journal article or published institutional reports at the time this review was completed) were excluded.

In an effort to remain concise, the focus of this manuscript remains directed toward the state-of-the-art methods for trip generation estimation, particularly for urban contexts. Description of state-of-the-practice can be found in the ITE *Trip Generation*

*Handbook*, which is now in its third edition (2014). The following subsection provides context for the applications of trip generation data. An overview of the general state-of-the-art methods for estimation of urban-centric transportation impacts is provided, including a table describing the methods evaluated in this study (see Table 2-1 through Table 2-3). This manuscript ends with a longer discussion section focusing on comparing these methods for consistencies with travel behavior and economic theories, and conclusions for moving forward.

### ***Applications of Trip Generation Data & Methods***

The question of how to properly estimate the multimodal transportation impacts of urban development is more pressing as urban areas struggle with the challenge of creating sustainable futures, supporting multimodal development, and reducing greenhouse gas emissions from the transportation sector given ever-constrained public resources. And as performance measures evolve, so must the data (Governor's Office of Planning and Research 2016). Because the current methods for estimating transportation impacts rely on these existing methods that have been shown to have varying applicability and accuracy in urban areas (Shafizadeh et al. 2012; Millard-Ball 2015; Weinberger et al. 2015), the implications trickle down into many different components of engineering and planning for new development, including site design, traffic impacts, system development charges, impact fees, emissions estimates, and sometimes regional travel-demand modeling.

The use of trip generation data has a broad set of applications in transportation engineering and planning. The first, and most well-known application, is the use of trip

generation data in TIA. Trip generation data refers to the counts of people entering and exiting a site. As with many studies of trip generation data, this manuscript will refer to trip “ends” as trip counts interchangeably. Trip generation data are used to estimate the relevant demand of new development or re-development, estimating “new trips” derived from new development, and providing an estimate of total impact that allows for an assessment of future travel at the site for the year of build-out relative to area-wide rates of growth (which are also sometimes estimated using trip generation rates (McRae, Bloomberg, and Muldoon 2006)). Many agencies in the US rely on ITE’s approach as a defensible method for assessing the impacts of new development (Clifton, Currans, and Muhs 2015; Bochner et al. 2011).

Trip generation rates are also used as a proxy to estimate whether or not the developer needs to conduct a full TIA (Clifton, Currans, and Muhs 2012). If a new development is estimated to produce more than the threshold number of vehicle trips, as outlined by a given agency, the process triggers a TIA to review the relevant impacts of the new development. The thresholds that trigger TIA are often arbitrarily chosen—occasionally specified differently for districts throughout the city. For most agencies, only vehicle-oriented triggers are used. Some have suggested the use of non-motorized- or transit-based triggers that may encourage more thorough multimodal development review, particularly in evaluating the safety of non-motorized modes of travel surrounding the development (Ridgway and Tabibnia 1999).

Although the original intent of creating a compilation of trip generation was for use in traffic impact analyses, it is far from the only application of these data. As such,

the implications of imprecision, inaccuracy, and inappropriate applications extends far beyond site-level traffic mitigations. Vehicle trip generation rates have also been used to estimate system development or impact fees—to accommodate improvements in network capacity or service—and transportation utility fees—to account for costs of operation and maintenance. While practices in applying impact and utility fees vary, these transportation charges are often applied on a “per trip basis” which are estimated based on ITE’s data and methods, e.g. (Junge and Levinson 2012).

And while these data are occasionally used within four-step travel-demand models to produce attraction trip generation rates—specifically for special generators or where there exists limited household travel survey data—they have been more recently incorporated in models estimating emissions of development in California. The CalEEMod model estimates greenhouse gas emissions for personal vehicle travel at new developments using a combination of ITE trip generation rates and locally derived trip length distributions (ENVIRON International Corporation and the California Air Districts 2013), allowing users to evaluate greenhouse gases through vehicle miles traveled to satisfy Senate Bill 743 on Environmental Quality.

### **Urban Estimation: A Paradigm Shift**

As researchers and agencies become more interested in improving traffic impact analyses for their regions, there has been a shift in the type of trip generation data collected. Alternative trip generation sources include person-trip rates, mode shares (and mode-specific count estimates), contextual information (e.g., density, diversity, design, multimodal facilities, parking, socio-demographics), site information in addition to the

“size” of the development (e.g., the cost of dwelling units, bike parking, year built, transportation demand management (TDM) strategies). Moreover, as more agencies are the drivers of funding data collection and method revision research, some are also requiring that as much of the site-level information be both free and readily available for researchers, developers, and practitioners.

Multimodal trip counts cannot always be easily collected using observation or passive data collection—such as cordon counts. The state-of-the-practice for collecting multimodal trip counts relies on both person counts entering and exiting the site to establish an overall person-trip rate, and a visitor intercept survey to calculate a multimodal mode share and an automobile occupancy rate. The combination of the person-trip rate, mode share, and automobile occupancy rate provides an estimate of multimodal person-trip counts and rates (e.g., person trips by car, bike, walk, transit, and vehicle trips). Additional information is sometimes collected but not always provided along with the cleaned data; this data may include on-street or off-street automobile/bike parking of visitors, trip length, trip purpose, demographics (age, gender, or income), group size, frequency of site visit, and frequency of mode used (Clifton, Currans, and Muhs 2013).

Although the procedures from person trip generation data collection are far from widely adopted by agencies across the United States, ITE’s *Handbook* has adopted some of the suggestions for guidance based on a few papers derived from recent research with common features. ITE’s most recent addition of the *Handbook* included methods to collect multimodal person-based trip generation for infill development—single land uses

developed on unused or vacant land within urban areas that are already mostly developed (Institute of Transportation Engineers 2014)—and are planning increased updates later this year (Bochner et al. 2016). The data collection methods adopted reflected the input of authors of several recent papers and data collections. These revised guidelines do not recommend a unified method to account for differences in urban behavior, but rather introduce multimodal assessment using a wide range of approaches, each with its own limitations and constraints.

There are 13 methods available (per my review standards stated in the introduction) and tested to predict urban vehicle trip generation impacts. To simplify the discussion, the following cited methods have been labeled in no particular order by letters. The characteristics of each method are described in Table 2-1 through Table 2-3. The methods discussed in this paper, with their corresponding reference letter, include:

- A. Urban Context Adjustment (Clifton, Currans, and Muhs 2015)
- B. Smart Growth Trip Generation Adjustment (Schneider, Shafizadeh, and Handy 2015)
- C. Household Travel Survey Urban Context Adjustment (Currans and Clifton 2015); based on (Clifton et al. 2012)
- D. Report 758, National Cooperative Highway Research Program (NCHRP) (Daisa et al. 2013)
- E. Report 684, NCHRP (Bochner et al. 2011), an updated version of the ITE's Multiuse Method (Institute of Transportation Engineers 2004) not discussed here
- F. Environmental Protection Agency, MXD (Ewing et al. 2011); based on (Ewing, Dumbaugh, and Brown 2001)
- G. MXD + (Walters, Bochner, and Ewing 2013)
- H. Report 128, Transit Cooperative Research Program (TCRP) (Cervero and Arrington 2008)
- I. URBEMIS (Nelson/Nygaard 2005)
- J. CalEEMod (ENVIRON International Corporation and the California Air Districts 2013)

- K. San Francisco Traffic Impact Guidelines (The Planning Department: City and County of San Francisco 2002)
- L. New York City (NYC) Transportation Guidelines (New York City 2014)
- M. Washington, DC, Department of Transportation (DDOT) (Ewing et al. 2017)

To the author's knowledge, there are also currently nine large research projects in progress across the US designed with the intent to improve our understanding of how transportation impacts vary in transit-oriented development,<sup>3</sup> smart growth areas,<sup>4</sup> areas that allow no new parking to be included in new development,<sup>5</sup> developing more locally sensitive rates,<sup>6</sup> affordable housing with transportation demand management strategies,<sup>7</sup> as well as one focusing on how to identify which method is best suited for different environments.<sup>8</sup>

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<sup>3</sup> Two projects funded by the National Institute for Transportation and Communities (NITC), led by Reid Ewing from the University of Utah; and Air Resource Board, led by Maggie Witt

<sup>4</sup> Projects funded by the California Department of Transportation (Caltrans), led by Brian Bochner of the Texas A&M Transportation Institute (TTI).

<sup>5</sup> Project funded by the National Institute for Transportation and Communities (NITC), led by Kelly J. Clifton of Portland State University.

<sup>6</sup> Two projects funded by: New York City, and San Francisco.

<sup>7</sup> Two projects funded by: Caltrans, led by Kelly J. Clifton of Portland State University; and City of Los Angeles, led by David Somers.

<sup>8</sup> Project funded by the Virginia Department of Transportation (VDOT), led by Ilona Kastenhofer of VDOT.

While most of these studies have collected or will collect urban trip generation, there remain only three methods that directly estimates person trips. While a few methods utilize household travel survey data, organized in a format that allows for parity with more traditional methods, for most methods, there exist too few person counts for any one land use to estimate multimodal impacts directly from establishment level studies and control for the various aspects of new development believed to influence transportation impacts (such as the built environment, sociodemographics, etc.). As it stands, most existing methods that account for any of these issues are adjustments—modifying ITE’s suburban, vehicle-oriented data and methods, most often to correct for relative measures of the built environment.

The most common way to estimate person-trip rates is to indirectly adjust ITE’s *Trip Generation Handbook* vehicle trip generation rates based on assumed mode share and vehicle occupancy rates for ITE’s study sites. This adjustment method considers ITE’s *Handbook* study sites, and assumes an automobile mode share and a vehicle occupancy rate for these ITE-type locations. The range of assumed automobile mode share rates varies by land uses, but is generally considered between 95- and 100% of automobile uses based on the vehicle-oriented, suburban, single-use establishment descriptions within the *Handbook*. Transit use was not collected very often in ITE’s baseline sites, but occasionally it was recorded and can be used to adjust these assumptions. Vehicle occupancy rates were reported for only a select few land uses, but can be used to refine the general assumption of vehicle occupancy rates between 1.0 to 1.2 persons per vehicle. The ITE vehicle trip estimation is then adjusted using these

assumed rates to derive a person trip estimate (see Equation 2-1 for the mathematical form of this description).

**Equation 2-1 Adjusting ITE Vehicle-trip rates into ITE Person-Trip Rates**

*Person Trip Estimate*<sub>ITE</sub>

$$= \frac{\textit{Vehicle Trip Estimate}_{ITE} * \textit{Vehicle Occupancy Assumption}_{ITE}}{\textit{Automobile Mode Share Assumption}_{ITE}}$$

This estimate, generally derived using loosely assumed mode share and occupancy rates, represents the person-trip rate of ITE-type locations—suburban, vehicle-oriented, single use locations with no shared parking, little to no transit access, and no bicycle or pedestrian activity. These person-trip rates are assumed constant across urban contexts, or rather the assumption is that an estimate of person trips derived from ITE’s suburban sites is relevant for more urban locations as well. The implications of this assumption are discussed in the sub-section Estimating People. However, for study sites in urban contexts, this ITE-based estimate of person-trip rates is used to estimate overall activity, and then context-based estimates for the urban area are used to determine the mode share for the study area, allocating the person-trip count estimates into relative mode counts (see Equation 2-2 for the mathematical form of this description).

**Equation 2-2 Reallocating ITE Person-trip rates into Context-Based Modal Trip Estimates**

*Trip Estimate*<sub>context,mode</sub>

$$= \frac{\textit{Person Trip Estimate}_{ITE} * \textit{Mode Share Estimate}_{context,mode}}{\textit{Vehicle Occupancy Estimate}_{context,mode}}$$

While the industry shifts toward collecting multimodal trip generation data, practitioners continue to struggle estimating the impacts of urban development. In lieu of waiting for person-based trip generation estimation methods to become available, the industry remains reliant on methods that adjust vehicle trip generation—most often estimated using ITE’s *Trip Generation Handbook*. These adjustments are developed from urban trip generation data or they are developed using secondary household travel survey data. Eleven of the thirteen major adjustment methods discussed here rely on some “base estimate” adjustment—always on ITE’s *Trip Generation Handbook* vehicle trip generation rates, but sometimes allows for some locally collected data. Table 2-1 through Table 2-3 provides a summary of all 13 methods for urban trip generation estimation. The following section provides a discussion of the similarities and differences between these methods, aligning the research with themes and theories of travel behavior and urban economics.

**Table 2-1 Urban Trip Generation Estimation Methods, table 1 of 3**

Method ID:	Type of Data <sup>a</sup>	Adjustment to ITE's Estimates	Provides Predictions for:						Region of Data used for Model Development
			Vehicle Trips	Person Trips	Person Trips by Mode	Mode Share	Vehicle Occupancy	Trip Length	
<b>A</b>	Site	Yes	Yes						Portland
<b>B</b>	Site	Yes	Yes						California
<b>C</b>	HTS	Yes	Yes			Yes	Yes		Portland, Seattle, Baltimore
<b>D</b>	HTS	Yes	Yes			Yes			Any
<b>E</b>	Site	Yes	Yes			Yes			Texas, Florida
<b>F</b>	HTS	Yes	Yes			Yes	Yes	Yes	Atlanta, Boston, Houston, Portland, Sacramento, Seattle
<b>G</b>	Site	Yes	Yes			Yes	Yes	Yes	Atlanta, Boston, Houston, Portland, Sacramento, Seattle, Texas, Florida
<b>H</b>	Site		Yes		Yes				Portland, Philadelphia, New Jersey, Washington DC, San Francisco
<b>I</b>	Elasticities	Yes	Yes			Yes	Yes		Any
<b>J</b>	Site/HTS/other	Yes	Yes			Yes	Yes	Yes	California, or Any
<b>K</b>	Site	Yes	Yes			Yes	Yes		San Francisco
<b>L</b>	Site		Yes	Yes					New York City
<b>M</b>	Site		Yes	Yes	Yes				Washington, DC

<sup>a</sup> Site: travel behavior observed at individual sites; HTS: Household travel survey data; Elasticities: derived from external and prior studies; other: allows external data, assumptions and information to be incorporated into model estimates.

**Table 2-2 Urban Trip Generation Estimation Methods, table 2 of 3**

<b>Method ID:</b>	<b>Area Type <sup>b</sup></b>	<b>Ready to Use</b>	<b>Time of Day <sup>c</sup></b>	<b>Land-use types</b>
<b>A</b>	Infill	Yes	PM	High-turnover (sit-down) restaurants; Convenience markets; Drinking places
<b>B</b>	Infill	Yes	AM/PM	Mid- to high-density residential; Office; Coffee-donut; Multi-use development; Retail; Other
<b>C</b>	Infill +	Yes	AM/PM/Daily	Restaurant; Service (non-restaurant); Retail; Office; General residential; Single-family residential; Multi-family residential; All land uses pooled
<b>D</b>	Infill +	No	AM/PM/Daily	User defined
<b>E</b>	MXD	Yes	AM/PM	Retail; Restaurant; Office; Hotel; Cinema; Residential
<b>F</b>	MXD	Yes	AM/PM/Daily	Employment (office, industrial, retail); Residential Population
<b>G</b>	MXD	Yes	AM/PM/Daily	Any application of Methods E or F
<b>H</b>	TOD		AM/PM	Multifamily Housing
<b>I</b>	Flex	Yes	Daily	ITE Categories
<b>J</b>	Flex	Yes	Daily	ITE Categories
<b>K</b>		Yes	PM/Daily	ITE Categories
<b>L</b>		Yes	AM/PM/Daily	ITE Categories
<b>M</b>	Infill/MXD	Yes	AM/PM	Multifamily Residential; Lodging

<sup>b</sup> Infill +: may be applicable to larger areas that are not single-use; MXD: mixed use development; TOD: Transit-oriented development; Flexible: method is flexible to development type.

<sup>c</sup> General definitions include, AM: peak hour 7AM-9AM; PM: peak hour 4PM-6PM; Daily: 24-hour counts

**Table 2-3 Urban Trip Generation Estimation Methods, table 3 of 3**

<b>Method ID:</b>	<b>Built Environment</b>	<b>Parking <sup>d</sup></b>	<b>Demographic <sup>e</sup></b>	<b>Internal Capture <sup>f</sup></b>
<b>A</b>	Several univariate relationships are provided.			---
<b>B</b>	“Smart Location” Index developed from multiple characteristics.	On-street	Area-wide	---
<b>C</b>	Various measures tested; strongest predictors included.			---
<b>D</b>	None			---
<b>E</b>	None			Yes
<b>F</b>	Various measures tested; strongest predictors included.		Trip-maker	Yes
<b>G</b>	Various measures tested; strongest predictors included.		Trip-maker	Yes
<b>H</b>	Various measures tested and provided.			---
<b>I</b>	Various relationship discussed and provided.	Supply/Price		---
<b>J</b>	Local information can be substituted to control for context.			---
<b>K</b>	Rates Segmented by District.		Land use	---
<b>L</b>	No context for rates; Mode share to be compiled according to local context.			---
<b>M</b>	Densities relatively constant in study area			---

<sup>d</sup> On-street parking: indicator for on-street parking present; Supply/Price: elasticities for constrained supply or parking pricing pulled from prior studies.

<sup>e</sup> Area-wide: indicates variables describing the surrounding area of the development, such as the block group area of study location; Trip-maker: indicates characteristics of observed trip-makers were incorporated into the method development; Land Use: indicates characteristics of the nature of the land use itself (e.g., “luxury condominiums” or “discount grocery store”)

<sup>f</sup> Internal capture is only relevant for mixed-use developments; methods developed for infill, but not listed as mixed use, do not provide a means for estimated internal capture.

## **Discussion: State-of-the-Art Methods**

The methods summarized in these tables are explored below with respect to several elements of urban trip generation estimation, travel behavior theory, and urban transportation economics. The methods—identified using the ID’s provided in these tables—and their relative contributions and performances are discussed in this section. Among these methods, there is no clear indication that any of these methods do a better job of estimating urban influences in trip generation—e.g. (Shafizadeh et al. 2012; Weinberger et al. 2015)—likely due to limited data, so instead, the focus for this study is on the relationship between these approaches and travel behavior, land-use development, and economic theories.

### *Estimating People*

The three of the 13 urban methods that estimate person-trip rates directly (K, L, M) are agencies that have compiled their own data repository. The other nine methods adjust ITE’s vehicle-trip rates either (a) directly adjusting vehicle-trip rates for urban context through reductions in vehicle trips (A, B) or (b) adjusting from a baseline estimated person-trip rate derived from ITE’s suburban rates. In these nine methods, there are no adjustments for changes in person-trip rates across urban areas—adopting the assumption that person-trip rates are constant across all areas.

To explore this assumption, we first examine on the travel behavior literature. In reference to trip generation, most of the literature focuses on estimating the relationship between the built environment, demographics and mode-specific travel (e.g., vehicle trips, walk trips) (Ewing and Cervero 2010), mainly centered on travel described from a

home-based orientation which limits the ability to transfer findings to a wide range of development-types. While much can be explained from independent analyses of mode-specific travel, few studies have focused on understanding the overall demand for travel (e.g., total trips or activity)—or rather the joint effects of land use upon mode-choice and trip frequency—potentially leading to over- and underestimation of overall activity (Guo, Bhat, and Copperman 2007).

In lieu of substantial support from the travel behavior literature, we turn to urban economics. The theory of bid-rent has indicated that as regional accessibility decreases, so does the value of land, e.g. (Alonso 1964; Mills 1969; Giuliano and Small 1991). It follows that businesses pay a premium to locate in areas with higher levels of accessibility—defined as access to destinations or economic potential. Studies indicated that even residents pay more to locate in areas with: greater accessibility in terms of retail and total employment destinations (Kockelman 1998; Srour, Kockelman, and Dunn 2002); lower accessibility to workplace competition (Srour, Kockelman, and Dunn 2002); greater access to transportation facilities, such as highways (Iacono and Levinson 2012) or metro lines (Anas 1995), although some suggest there is no significantly added value in locating near multimodal facilities (including bicycle and pedestrian) (Iacono and Levinson 2011). Many studies have also found significant relationships between accessibility and employment (Srour, Kockelman, and Dunn 2002), retail (Srour, Kockelman, and Dunn 2002), business districts (Cervero and Duncan 2002), population (Srour, Kockelman, and Dunn 2002), transit (Anas 1995; Cervero and Duncan 2002) as well as toward facilities (Targa, Clifton, and Mahmassani 2005). More directly, the

success (sales) of the businesses—which must then off-set any premiums paid by increased accessibility of the location choice—is determined by: the regional accessibility (population accessible to the site), and the economic potential of the location (income of the population that may access the site, discussed later in this section) (Des Rosiers, Theriault, and Menetrier 2005).

Further research is necessary to determine whether the outcomes suggested by this theory hold for transportation impact studies—in other words, do person-trip rates vary by accessibility to destinations and consumers, land value, or the economic potential of sites? Instead, this theory calls into question the assumption that person-trip rates do not vary across contexts, which is prominent in nearly every state-of-the-art method. If regional accessibility is the metric that reflects how reachable the location is relative to other areas in the region—for which no existing study to the best of the author’s knowledge has tested—it is included in only three methods to capture variations mode share (C) or vehicle-trip rates (B, H). But none of these adjustments account (or test) for variation in *person-trip rates* across any definition of accessibility—even New York’s approach provides a single person-trip rate for all five boroughs. The approach used in San Francisco (K) indirectly accounts for regional accessibility (as well as demographics and densities) in the estimation of mode shares within predefined districts. The New York approach (L) for estimating mode share accounts for regional accessibility indirectly through qualitative assessment and selection of previously collected data for location-by-location application. Furthermore, understanding the overall flows of activity to and from any one development requires a better understanding of *who* is traveling in the first place,

which leads us to examine the ways in which demographics are incorporated into site-level transportation impact estimation methods.

*Who the people are*

Few methods account for socio- or economic-demographic indicators. There are two ways to incorporate demographics in trip generation analysis: studying the trip-makers or studying the market in the study area. The former approach is not utilized in any of the methods (except for an early version of the method C where mode share varied significantly with income (Clifton et al. 2012)), mainly because citing issues in the practical application is difficult when we do not know who may be coming to the sites. The alternative method to account for demographics is to use some average or median values representing the site's surrounding areas. While developing the Smart Growth Trip Generation adjustment (B) and EPA MXD (F), contextual information about the types of average households located within the mixed-use development study area—including children, household size, and vehicle ownership—were included. For adjustment B, there was not enough evidence to suggest the variables were significant. For adjustment F, there was evidence to suggest the variables were significant; analysts applying the model rely on area-wide descriptions of demographics to apply adjustments. Methods D and K use district-based analysis to estimate mode shares—the benefit being that relative-difference in travel behavior due to trip-maker demographics are incorporated indirectly through aggregation of trips that occur in those areas. For example, trips from districts with high-land-values reflect trip-maker decisions that would normally travel to high-land-value districts.

To fully understand the travel demand, we must also understand who is traveling and why. Within the theory of derived demand, it is recognized that activity patterns of individuals and households are constrained in both time and monetary budgets, requiring certain types of activities to satisfy both individual and household needs, but constraining travel to activities—as well as the activity itself—within time and cost budgets (Bhat and Koppelman 1993; Goulias, Pendyala, and Kitamura 1994). Activities are correlated among members of a household, particularly among households with children whose dependence is so great, and shifts of activity patterns for every member of the household can be seen (Pas 1985). In practice, trip generation studies rarely consider the socio-demographics of the establishment's market. Without information about who is traveling to these establishments, there is a limited ability to control for specific variations in demographics using existing data.

An alternative to accounting for demographics using explicit variables in analysis is to incorporate the measure in how the land use is defined (e.g., luxury condominiums, discount superstores or grocery stores, toy/children's store, baby store) (Institute of Transportation Engineers 2012) although this segmentation may be a statistically inefficient use of the data—the description of how these categories were defined is not publicly documented. San Francisco (K) segments residential land-use types by the number of bedrooms, attempting to capture variations in household size of the residents. ITE considers luxury condominiums as a separate category from condominiums and includes a “discount grocery store” category (Institute of Transportation Engineers 2012) although the definition for luxury and discount in monetary terms is not provided. We are

left to assume that any data in the land-use category not specified by some measure of price are actually market rate, but this information is neither solicited nor regularly collected for uses prior to creating these categories, making demographic-based adjustments to ITE impractical.

There is a substantial amount of interest in investigating the relationship between trip-maker behavior and socio- or economic-demographics for development-level evaluation of transportation impacts—particularly related to multifamily housing, income, and vehicle ownership.<sup>2,4,6</sup>

#### *Land Use Categorization and Aggregation*

Next, the detailed categorization of ITE's land-use classification needs consideration. ITE's *Handbook* divides their data into over 150 different definitions of land use, with little published discussion about the process in which new categories are added or aggregated and whether that level of cataloging is necessary for practice. It is not clear whether the process of aggregation is based on the definition of land use alone, or on some form of statistical testing of behavior. Regardless, methods that directly adjust ITE's vehicle-trip rates rely heavily on ITE's detailed categorization of land-use types (A, B, C, I, K, L), while methods that use household travel survey data (C, D, F), or that are constrained by too few data (E), aggregate land use categorization into broader designations that reflect zoning definitions (e.g., retail, service, residential). Since the user of these data are often the developer—and the stage of development review often only provides a rough estimate (Keller and Mehra 1985b) not always corresponding with

the final product (McRae, Bloomberg, and Muldoon 2006)—the (dis)aggregation of categories plays a big role in how efficiently these data are used.

Recalling our discussion of “derived demand” in the previous subsection, the incentive for studying the trip-maker’s motivations for activities results in a more complete understanding of why variations in travel behavior are observed and how better estimates or predictions of it can be obtained. Based on this view of travel, more attention should be paid to the reasons for the demand for activities themselves, and the corresponding derived nature of travel (Pas 1985). The result could be a land-use taxonomy for trip generation estimation at the establishment-level that is based in the theory of derived demand, supported by activity-based research and theory, and considerate of applied practice and the multidimensional information available to predicting land-use types at new developments (Guttenberg 2002; American Planning Association 2001). By considering the patterns of travel behavior and motivations related to specific types of activities, potential similarities and differences between land uses can begin to be identified to pinpoint patterns of behavior that allow more accurate and precise predictions of transportation impacts of development.

### ***Built Environment and Multimodal Travel***

Some previous research suggests that travel behavior varies across different measures of the built environment (Ewing and Cervero 2010). The built environment may include any of the six D’s: density, (land-use) diversity, design, destinations, distance to transit, demand management (Cervero and Kockelman 1997; Walters, Bochner, and Ewing 2013). (The seventh D, development scale, is accounted for in both

the categorizing of mixed-use and infill development and development size. The eighth D, demographics, is discussed in the previous subsection.) Although there is a lack of consensus for whether behavior, such as mode choice and trip rates, do vary by the built environment (Ewing and Cervero 2010), 10 methods evaluated here include the built environment in their estimation process, placing a great importance of urban context in estimating variations in trip generation—specifically as it pertains to changes in mode shares or mode-specific trips.

Household travel surveys are commonly used to estimate multimodal mode share and vehicle occupancy rates (C, D, F, G, I, J, K, L). Alternatively, methods can utilize intercept surveys performed during the site-level data collection (E, G, L), but these data are both expensive to collect and difficult to synthesize for future use. In New York (L), mode shares are not attached to person trip generation rates, but provided location-by-location based on the land use and urban context of the development. In Washington, DC (M), due to small variation in densities, multimodal trips are estimated as a function of development size, without regard to variation in the built environment.

Only two methods account for TDM strategies (beyond transit access): metered parking within 0.1-miles of the development (B); proportion of surface parking (B); and various transportation demand management programs (I). Agencies, like San Francisco (K) and New York City (L), often negotiate credits for adopting strategies allocated through a separate process. NCHRP 684 (E) includes a small sample of study sites (six), but uses proportions of land uses to interpolate potential mixing of land uses. The combination of NCHRP 684 with EPA MXD (F) into MXD+ (G) allows the user to

control for variations in mode share based on a wider sample of sites and built environments provided by household travel surveys used in EPA MXD while maintaining the robust analysis of how trips within developments are captured by other land uses. These methods are discussed in the following subsection. Seven methods account for the built environment using either continuous measures describing the built environment (A, C, F, G, H, I) or a distilled measure using factor analysis (B). Two methods (D, K) account for the built environment by using districts or zones to estimate variations in mode shares.

#### *Mixed-use or Multi-use Methods*

Adopted in the second edition of the *Handbook* (Institute of Transportation Engineers 2004), ITE incorporated a method to estimate impact adjustments for mixed-used development. A mixed-use development (sometimes called a multiuse development) is defined as “an integrated development (usually master planned) consisting of at least two complementary and interactive land uses designed to foster synergy among activities generated by the land uses” (Institute of Transportation Engineers 2014, 138). Literature discussing mixed-use developments, trip generation, and internal capture tends to reflect the data analysis of large planned communities. By ITE’s definition, however, the scale of these developments tends to include mostly single developments (planned simultaneously, but built out in stages), ranging from 7 to 300 acres in scale (Bochner et al. 2011), but other comparable studies have even focused on developments anywhere between 5 to over 2,000 acres (Sandag 2010; Ewing et al. 2011). In mixed-use development analysis, “internal capture” is defined as “a person trip made between two

distinct on-site land-uses at a mixed-use site without using an off-site road system” (Institute of Transportation Engineers 2014, 129). This type of trip can be made by any type of transportation mode.

By removing trips that are internally captured from the overall estimate of transportation demand, the estimate reflects trips that are added to the existing network after the development occurs. For new development (or re-zoned development), this means that only the change in transportation demand, before and after development, is used to assess the impacts—either through impact fees or charges, or when evaluating necessary mitigations to the adjacent transportation network (e.g., roadway widening, turning bays, intersection upgrades). For mixed-use development, ignoring internal capture would result in over-development for the automobile—which inhibits precisely the goal that mixed-use developments are trying to achieve: walkable, connected, planned neighborhoods. Similarly, for infill development, analysts also assume that a proportion of travel to new development is “pass-by” traffic, or does not necessarily add traffic to the network. The methods of collecting and applying pass-by data were not subject for review in this study.

Three methods (E, F, G) were established for mixed-use developments, ranging from single-building developments (F, G) to 800-acre planned development, and these methods account for whether person trips (by automobile, foot, bicycle, or transit) generated to the study area are external or internal. Because NCHRP 684 (E) was developed using site-level data from only six locations, the authors combined their estimates with the results provided from EPA MXD (F) to derive reconciled estimates in

MXD+ (G). The other methods mentioned in Table 2-1 through Table 2-3 are primarily for infill, although each of these methods on their own can be used to estimate establishment rates (although not internal capture) located within mixed-use development to refine rate estimates.

Hooper et al. (1990) and Bochner et al. (2011) have set the standard for mixed-use and multiuse development data collection at large (3 to 800 acre) mixed-used developments. They approach the complexity of capturing the internal trips between land uses within the development with a system of: cordon counts (automobiles); *Manual* person counts; intercept surveys at establishments and transit access points; and intercept surveys along internal sidewalks. These data collections are often the most expensive to perform—costing upwards of \$50,000 per site (Bochner et al. 2011)—and therefore are much harder to find than single-use or single-building sites (as much as \$10,000 per site).<sup>2</sup>

The term “mixed-use development,” however, includes a broader definition in practice than considered in ITE-related studies. Mixed-use development includes any area where the mix of land uses results in trip chaining between the land uses. While there is a growing literature on the overall transportation impacts of mixed-use planned developments towards an analysis that examines the influences of mixed uses on infill development within existing communities—we understand less about how these infill developments function within an existing mixed-use community—like historic downtowns, urban commercial corridors, or the central business district. Authors in a 2013 study surveyed visitors to shopping districts in suburban and urban areas and found

that 65% of trips between land uses in all shopping districts were walking trips, but in urban centers, approximately 96% of trips between land uses were walking trips (Schneider 2013). Furthermore, an understanding of the ways in which trips are captured within mixed-use buildings has just begun to emerge (Walters, Bochner, and Ewing 2013), but the available methods have not been adequately tested within a dense urban range of contexts—particularly because of the extensive costs of data collection. As such, new approaches to capturing and understanding the interactions between infill development and the surrounding existing area are needed.

## **Conclusions**

Trip generation estimation methods for transportation impact analyses were developed with an eye for simplicity—a quick rule-of-thumb reference—but estimating transportation demand is more complex and nuanced than methods in practice suggest. Research developed in response to this review may increase the flexibility of the data available for practice, extending the life of information by being more efficient in how it is understood and being used. This will allow agencies, developers, and practitioners to recognize which elements of a new development and its environment might influence the expected transportation impacts, permitting more appropriate mitigations to be considered to achieve planned results. This review identifies methods eligible for transportation impact analyses, providing a critique in the successes of existing methods, as well as the gaps supported by the literature.

The findings of this review indicate strong support for understanding the influences of the built environment on vehicular trips, but not necessarily on multimodal

trips. The assumptions used for most of the existing methods—adjustments to ITE’s method—have not been tested for conflicts with theories of urban economics, such as (Alonso 1964, Des Rosiers, Theriault and Menetrier 2005), to the best of the author’s knowledge. There appears to be little-to-no sensitivity towards the relationship between the sociodemographic of the trip-maker and behavior for TIA, which may cause over- or under-estimation of vehicle travel in areas on either end of the income distribution. Moreover, the current detailed segmentation of land-use categories may not provide any additional benefit for evaluating new development, particularly as the TIA process is held very early in the development stage. Moreover, detailed accounts of the businesses occupying the development may not be known. Overall, the gaps identified from this review of state-of-the-art methods suggests consistencies with travel behavior theory related to identifying likely trip-makers—sociodemographic and economic constraints that define a time and monetary budget for travel to land-use development. While the extent of the corresponding biases for these issues is yet unknown, multiple existing and on-going projects aim to target several of these problematic areas.

Although this study identified several gaps and issues in this process, primed for future research, the responsiveness to these themes in state-of-the-art methods in urban transportation impact analysis has improved substantially within the past two decades. However, there has been little effort in the literature to identify the widespread use, substitution or replacement of existing methods in practice. These findings suggest only a limited and anecdotal view of the state-of-the-practice of transportation impact study approaches.

While this manuscript has focused upon existing, peer-reviewed and published methods for estimating urban trip generation for TIA, many new forms of data have become more readily available to agencies and analysts. While ITE has only recently accepted and incorporated adjustment methods developed from more traditional and pervasive household travel surveys into use, there remains an ever-growing list of new technologies that may be applicable to such circumstances. Examples of which include, but are not limited to: smart phone tracking data and “push” surveys, transaction count data, Google data like “popular times” activity distributions, and passive-data-collection technology including Bluetooth tracking and various forms of sensors. Likewise, the need for responsiveness in urban trip generation methods to planning policy goals and indicators requires the merging of multiple forms of data to describe urban form, transportation facility pricing, and, not the least of which, parking. Few methods consider and explore the endogeneity of parking availability and pricing in vehicle and multimodal trip generation estimation. The practicality and effectiveness of these types of data in site-level impact analyses will be directly related to the capacity, support, and willingness of agencies to test and adopt new technologies that may improve accuracy and precision, as well as the theoretical understanding of transportation impacts at urban land-use development.

Additionally, few have discussed the uncertainty and limited information available to developers and analysts during the time many TIA are completed. Many building permits are tied up in the process of site-level evaluation, leaving impact fee estimates and TIA studies tied up in rough predictions of what the development may

become. McRae et al. (2006) reviewed 12 TIA studies after development and found that 4 were not developed as planned in the TIA. This, combined with the inherent uncertainty existing in all transportation demand modeling predictions, leads to the question: Is it reasonable to evaluate new development so early in the development process and per estimates from models not necessarily sensitive to planned outcomes seen as influencing behavior? Or rather, should the evaluation of impacts along a singular metric of trip generation—that so often leads to incremental over-development of automobile facilities (Manville 2017), regularly in direct conflict with regional plans—be the primary means of determining whether mitigations to the network be made? This is certainly a necessary area of future research and thought.

The methods available today, albeit adjustments to existing data of limited contexts, provide a means for planners and engineers, agencies and practitioners, to respond more flexibly toward planning outcomes, specifically the built environment. That said, there exists only limited evaluation of the performance and improvement of these methods for wide-spread applications practice. Expanding and improving evaluation may orient the user toward methods that perform better for their specific contexts or land uses. Furthermore, more could be done to assess how these approaches are being adopted, substituted, tailored for local context, or even prohibited by agencies and practitioners around the United States. As such, one of the main objectives of this manuscript is to provide a landscape from which researchers, agencies, and practitioners can more directly aim to continue to move the state-of-the-art forward.

## **CHAPTER 3 THE COSTS AND BENEFITS OF EXTENSIVE LAND-USE TAXONOMY IN TRIP GENERATION FOR TRANSPORTATION IMPACT ANALYSES**

### **Introduction**

A substantial amount of recent research has been dedicated to improving methods available for transportation impact analyses (TIA)—focusing much of the attention on varying travel outcomes (Clifton, Currans, and Muhs 2013; Currans and Clifton 2015; Ewing et al. 2011), controlling for the built environment (Bochner et al. 2016; Clifton, Currans, and Muhs 2015; Schneider, Shafizadeh, and Handy 2015), parking (Schneider, Shafizadeh, and Handy 2015), transit access (Cervero and Arrington 2008; Clifton, Currans, and Muhs 2015; Schneider, Shafizadeh, and Handy 2015), and evaluating the accuracy of methods, both old and new (Shafizadeh et al. 2012; Weinberger et al. 2015). Few have evaluated continued use of the pre-existing definitions of land use themselves. As Hodge (1963) notes, the classification of data into nominal categories is often a precursor towards all other forms of measurement (e.g., ordinal, ratios, intervals, continuous measures)—making the definition and categorization of land use an understudied aspect of TIA methods research.

For transportation impact analyses or studies (TIAs or TISs) and underlying data, the categorization of land use is often taken for granted—arguably more than any other aspect. In the past, several years there have been considerable efforts expended toward improving methods commonly used for TIA of new development, e.g., (Bochner et al. 2016). Urban agencies have created a demand for new tools and data with sensitivity for

urban-planning-policy objectives, including a broader range of outcomes (e.g., person trips, mode share, vehicle occupancy, trip length) and inputs (e.g., activity density, mixed use, and parking supply and pricing). Correspondingly, the Institute of Transportation Engineers—the predominant resource supplying these data and methods—has published a revised *Handbook* working to incorporate the growing volume of studies aimed at addressing this gap in practice (Institute of Transportation Engineers 2014), with the intention of updating it in the coming year (Bochner et al. 2016) aimed at improving aspects often criticized—transparency, contextual information and variables, and guidance for applications in urban areas. Examining the categorization of land use should be an important part of this process.

There are indirect benefits for this evaluation of land use definitions. An overly detailed and ad hoc categorization of land uses may lead to a false sense of precision, and an expensive one at that. Transportation impact studies are often conducted and timed with the building permit. Not all developers have the ability to pin-point the specific land uses occupying a commercial space at the time of building development. Over-specification and -segmentation of land use reduces the sample sizes used to identify rates and limits the user to a single independent variable (size of the development), and requires more data collection for a longer list of categories. The application of detailed taxonomy seems like a more robust way to provide accurate estimates, but if specific categories are truly different than more generalized definitions, analysts may assume a false sense of precision by using specific codes. Additional features of land use—such as drive through access or product types—are then controlled for further segmentation of the

data into additional categories. If “new” land uses are identified, this process requires new land-use categories which are then made up of small sample sizes. No publicly documented framework has been created for assessing behavior patterns to identify existing land use data that may fit the patterns at the “new uses.”

More strategic classification (or aggregation) of land use—with theoretical underpinnings—could allow for larger sample sizes within each category, supporting the use of additional variables to control for other important factors, such as urban context, demographics, transportation-demand-management strategies, and parking supply and price. Identifying the underlying behavior of these new land uses would provide a method of classifying land use by behavior.

Moreover, the ways in which individuals participate in activities, particularly commercial activities, are evolving. Purchases and activities that were once observed at brick-and-mortar stores or shopping centers are carried out online. They are shipped to the household within days and sometimes hours. Even certain work activities are becoming more untethered to traditional workplace locations—allowing participants to work from home coffee shops, restaurants, and parks. Furthermore, we have seen a number of new land-use categories show up in the past few years, including but not limited to: fast casual restaurants, fast fashion retailers, dining/grocery shopping hybrids, and marijuana dispensary facilities. For each of these land uses, new calls for data are issued, and accordingly, data is collected resulting in the development of more low-size samples for these new uses. By evaluating the underlying motivations behind travel to

these differing land uses, these methods might be better equipped to accommodate changing trends in activity and travel behavior.

This manuscript revisits the land-use categories defined within ITE's *Handbook*, traditionally containing vehicle-oriented, suburban guidance. The aim of this manuscript is to evaluate whether the current extensive classification of ITE's land uses is necessary—or even useful—or whether examining the statistical differences and similarities of behavioral patterns across categories would be more accurate. Here, this analysis aims to identify salient activities and social interactions of land uses that relate to varying trip generation rates. The primary source of data used in this analysis is also the main resource of data used in transportation impact assessments across the United States: ITE's vehicle trip generation rates. To narrow the scope of this manuscript, commercial land uses were the focus.

Two questions are explored: (1) how are vehicle-trip rates statistically different across ITE's land-use categories? And, (2) what benefits (and costs) are accrued from this extensive taxonomy? By evaluating the statistical difference between trip rates, the focus of these methods can be applied to prominent elements of new development that most correspond to differences in trip rates, while simplifying the process of identifying and classifying development early in the planning process. In addition, every decision in policy comes at a cost—the benefits of this taxonomy, therefore, are weighed against the costs.

The organization of this manuscript follows. First, we provide some context for this analysis. This study includes an overview of the background of transportation impact

studies and the data that corresponds with it (mainly, ITE's *Handbook*). We approach the literature review first from the broader context of land use classification for planning purposes, and then from an examination of travel behavior theories that explain why some behavior patterns are similar, and some are not. Then we explore the data and methods used in this manuscript to test these comparisons, followed by the results. This manuscript ends with a discussion of the results, incorporating the limitations of this analysis, recommendations for practice and next steps.

## **Background**

### ***Transportation Impact Analyses or Studies (TIAs or TISs)***

To offset potential impacts of new development, government agencies have long required developers to assess the transportation impacts of new development against performance metrics. This assessment, often denoted as traffic or transportation impact analyses or studies (TIA or TIS), these agencies then couple this evaluation with the requirements of corresponding mitigations necessary to prevent the failure of impacted transportation facilities, sharing the burden of improving the transportation network between the city and private developer. While there exists nationally available resources that explain, critique, or recommend different TIA practices, e.g., (Keller and Mehra 1985b; McRae, Bloomberg, and Muldoon 2006)—requirements vary across agencies and states—a general overview of TIA is provided here, with an emphasis on the relevancy of land use definitions.

A TIA is an assessment of the transportation impacts for which new or renovated development is responsible. It is generally required when the impacts are deemed significant in order for the developer and agency may share the growing burden of impacts. Not all development requires a TIA—many agencies provide a threshold against which development is compared to determine the need for more robust studies and evaluation.

Generally, an analyst estimates the overall “trips generated” to a site, removing some proportion estimated to be already “passing by” the development and, therefore, not included as new impacts. This estimate provides an approximation of new impacts. The remainder of trips are then allocated to the facilities extending away from the development. This process varies and may require more information about the distribution and flows of existing vehicle traffic as well as nearby land use—such as large housing developments or office parks—to assist the estimate for direction of travel. This estimated “traffic” derived from the new development is then added to the current traffic volumes, and the adjacent facilities are evaluated for potential failures in service. The agency, often through a negotiation between the developer and the agency, defines standards to determine which facility is evaluated (e.g., intersection signalization or timing, turning-bays, roadway width or lanes) and how far the scope of the study extends. The developer is often then required to assess the impacts of their development at each stage of the build out—and according to some forecasted timeline (e.g., three or more years) by assessing the development against projected nearby development and growth.

This process generally occurs early in the development process and is sometimes tied or associated with building permits. Developers may be developing the sites for their business or for tenants of other businesses. In the case of the former, the type of land use would be known (i.e., developers working on behalf of a grocery store chain would likely know what land use into which their project falls). However, if the latter were true, the developer likely only would be guessing at the land-use type (i.e., a developer developing a commercial development that may include services, retail, or office space would speculate who prospective tenants might be). This is complicated when the process of development review in question requires re-evaluation of impacts for change in tenants not originally covered under the first permit. A change in tenants may trigger another review—a potentially expensive process of analysis and mitigations that may inhibit smaller businesses from filling in vacant locations.

Finally, it is worth noting that the implications of this research, which focuses primarily—but not solely—on ITE’s *Handbook* data and methods, reach beyond TIA studies. Other types of site-level assessment are sometimes tied to new development, related in theory and method, but often not always in practice. Processes that rely on similar data and methods include—but are not limited to—computation of impact fees; system development charges; utility fees; or other monetary exactions; impacts of rezoning; and scaling or scoping projects. Greenhouse gas estimations (ENVIRON International Corporation and the California Air Districts 2013) are also reliant on these data as a starting point for estimating demand at non-household land uses.

### *Theory of Derived Demand and Travel Behavior*

Travel itself is fundamentally derived from the demand of activities at destinations (Kitamura 1988). On the conceptual level, this means that the travel observed when studying trip generation might be explained by the motivations of those who participate in the activities occurring at land uses. While we are examining vehicle trips in this manuscript, this could also include: the turnover of trips (how long the activity takes), the trip length, trip chaining (pass-by or diverted trips), and the frequency of trips made by any one person. To understand how travel varies, the theory of derived demand suggests that the motives for activity-participation—who travels for what, when, why, how and how much—should be the center of the investigation (Kitamura 1988; Pas 1985).

To segment and study activities and corresponding travel patterns, some travel behavior researchers and demand modelers categorize the nature or function of activities and trip purposes into three mutually exclusive and collectively exhaustive categories based on hierarchy of needs, e.g. (Bhat and Koppelman 1993; Reichman 1976): (a) mandatory or subsistence activities (namely work and work-related events), (b) maintenance or personal activities (e.g., those that satisfy biological and physiological needs), and (c) discretionary or leisure activities (e.g., entertainment, social, or recreational). This translates into the modeling of trip type (e.g., home-based, work-based, or other activity). It is worth noting that some researchers disagree with this stark segmentation of activities, questioning whether the psychological response to activities from each of these categories are the same for different people at different times or

whether activities might fit into a mix of categories for different people (Mokhtarian, Salomon, and Handy 2006).

Much of travel behavior research is determined to address these attributes of activity-based travel behavior working to uncover the dependent relationship between activities and travel. While many researchers have noted a lack in the literature that defines a causal relationship between activities and travel behavior (Ferrell 2005; Goulias, Pendyala, and Kitamura 1994), this theory of derived demand—and the corresponding activity-based analyses that followed—makes up the basis for the majority of travel behavior research to date (Marlon Boarnet and Crane 2001).

There exists only limited analyses of overall demand for specific activities (Crane 1996) that by extension can lead to the conclusion that there is also an incomplete understanding of the demand for activities at a more-refined level than the hierarchical classification of activities (e.g., sustenance, maintenance, and leisure). Moreover, because the majority of travel-behavior research focuses on individuals at a household-level of analysis instead of establishment-based, lessons associated with the literature raise potential questions to extend the analysis of establishment-based transportation impacts. Additional research is necessary to apply the theory of derived demand to the practice of establishment-based trip generation estimation.

### ***Activity-Based Considerations Testing a Revised TIA Taxonomy***

Within this section, categories of land use codes are identified based upon potential activity-based similarities in behavior (as classified within ITE's most recent *Trip Generation Handbook* (2014)) warranting further evaluation. The incentive for

studying the trip-maker's motivations for activities, results in a more complete understanding of why variations in behavior may be observed and how estimates might be improved from it. The purpose is to evaluate a land-use taxonomy for trip generation estimation at the establishment-level that is consistent with the theory of derived demand, supported by activity-based research and theory, and considerate of applications in practice and the multidimensional information available to predict land-use types at new developments (American Planning Association 2001; Guttenberg 2002). In this section we identify potential aggregations for ITE's land use definitions based on the activity and retailing literature. By considering the patterns of travel behavior and motivations related to specific types of activities, divisions in land uses may be identified and explained by patterns of behavior that allow us to more accurately and precisely predict transportation impacts of development.

First to illustrate this point, the influence of "convenience" land uses are examined. As Bhat & Koppleman suggest (1993), the relative levels of accessibility between residential land uses and commercial establishments reduces the burden on the trip-maker, in terms of travel time and costs. These factors, thus, increase the likelihood that trip-maker's will travel to accessible establishments. The description of land use may explain the difference between establishments oriented for quick stops (e.g., convenience markets, small coffee shops and restaurants, fast food stops) and those designed for a longer stay (e.g., sit-down restaurants, quality restaurants, supermarket). Although the market activity for the businesses is to satisfy maintenance and discretionary needs, their business model locates them in high-accessibility areas, which allow customers the

ability for stop-and-go activities. Examining the significance of similarities between “convenience” trip rates is one hypothesis tested in this manuscript.

There exist several limitations to the application of activity-based perspective to the practice trip generation estimation. Activity at different land uses across different times varies because the demand for those activities varies. Part of what constrains these variations are temporal and monetary constraints (Bhat and Koppelman 1993; Goulias, Pendyala, and Kitamura 1994). And these constraints are not limited to the individual’s daily activity requirements, needs, and wishes—the individual’s decision to travel (or not), participate (or not) happens in concert with the other household members (Goulias, Pendyala, and Kitamura 1994), particularly when children are present (Pas 1985). Detecting these relationships at an establishment-level is the primary aim of this study.

In the literature, there are many examples of how aspects of land use may influence the observed behavior at an establishment-level:

- *Activities of convenience* (Bhat and Koppelman 1993) (e.g., high-turnover, minor shopping and service);
- *Product base* (Brown 1992) (e.g., retail product base and relative market, or specialty, broad and narrow product ranges; small (clothing) versus large (furniture) products);
- *Size of development* (Brown 1992; Dunkley, Helling, and Sawicki 2004) (e.g., compare smaller restaurants with land uses of convenience, or compare larger restaurants with land uses of low-turnover retail);
- *Institutional format of similar products* (Brown 1992) (e.g., shopping centers, grocery stores, convenience markets);
- *Dependence of trip-maker* (Kitamura 1988; Pas 1985) (e.g., activities derived for markets dependent on others, elderly and children);
- *Social/recreational activities* (Mokhtarian, Salomon, and Handy 2006) (e.g., indoor versus outdoor recreation or exercise land uses, or movie cinema versus dining activities);
- *In-home and out-of-home substitutions* (Mokhtarian, Salomon, and Handy 2006; Salomon 1986) (e.g., eating outside of the home);

- *Temporally similar travel* (Clifton, Currans, and Muhs 2013) (e.g., cross temporal comparison of convenience activities (trip-chaining) that occurs during the AM versus PM peak commute);
- *Location of establishment within a development* (Bhat and Koppelman 1993; Brown 1992) (e.g., changes in trip rates due to potential trip-chaining, synergistic influences on rates, or shopping centers versus grocery stores, infill versus mixed use );
- *Activities influenced by friction-reducing technologies* (such as information and communications technologies [ICT]) (Ferrell 2005; Salomon 1986) (e.g., pre- and post- 2000 effects);
- *Sales philosophy* (Brown 1992; Clifton, Currans, and Muhs 2013) (e.g., how businesses market themselves in price, service or culture: luxury versus discount, family-friendly (large scale, seating) restaurants, age-specific markets);
- *Scale of business* (Brown 1992; Des Rosiers, Theriault, and Menetrier 2005) (e.g., national, regional and location chains of similar land-use types).

Note that most of these noted differences are unobservable at the establishment-level given ITE's typical descriptions. For example, not all restaurant trip rate data has information distinguishing sites with an excess of seating which might cater more towards leisure dining or low-turnover activities with those that seat smaller groups of customers which might indicate higher-turnover dining. The establishment name and brand as well as relative location within commercial districts or shopping centers are also not typically noted in trip generation reporting and are therefore not testable in this analysis.

### ***Temporal Changes in Land Use Definitions and Aging Data***

The interaction between trip-makers and land use have also evolved over time. For example, land uses responsive to innovations of ICT: as changes in ICT influence the availability of activities at new locations (e.g., in-home shopping, telecommuting from

coffee shops), there exists a shift in the amount of travel time and costs dedicated for certain types of trips, such as reduced work-related and shopping travel times. These shifts in behavior result in increased time available for other trips, potentially shifting demand to participate in other activities at other land uses (Ferrell 2005; Mokhtarian, Salomon, and Handy 2006; Salomon 1986). Time-crunched working women, for example, are a particularly latent market for online shopping. Telecommuting women who saved time on commute travel were more likely to perform travel-heavy routine shopping online—such as price-comparison shopping— instead of at a commercial land use, but this shifting in activity was reallocated to other maintenance activities, such as child care, appointments, and financial transactions (Gould, Golob, and Barwise 1998). In this example, the improvements in technologies over time suggest that behavior (in terms of trips) may have shifted for certain demographics from shopping to other activities—implying a temporal influence on trip rates due to the introduction of technologies. Banking is a clear example of a maintenance service that has transitioned toward becoming an in-home (or at-work or mobile-phone) activity. Trip generation has been so clearly influenced by these changes in ICT that it is currently the only land use in ITE's *Handbook* to have older data removed due to significant changes in overall trip rates (pre-2000) (Institute of Transportation Engineers 2014, 7–8).

ITE's data extends back to at least the 1960s (Institute of Transportation Engineers 2014). Changes in behavior overtime lead to problematic demand estimates by assuming the way people have traveled and interacted with land use in the past will be the same in the future. In an examination of the performance of transportation forecasts for

major projects, one leading cause for bias in estimates was “assumptions drag” (Flyvbjerg, Holm, and Buhl 2005)—where old data and assumptions were continued in use, despite quantitative evidence against the use of such information. Retaining these data implies that trip rates have not changed. In other words, there is an embedded assumption that vehicle trip generation rates have not changed over time.

### **Data – ITE’s *Handbook* Land-use taxonomy and Data**

Classification within the *Handbook* combines a complex set of land use definition to segment their data into nested and overlapping dimensions of land use: economic function (e.g., manufacturing, retail, services), activities based on business type and structure of (e.g., supermarket, sit-down (high-turnover) restaurant, arts-and-crafts store), product (e.g. pet supply superstore, baby superstore, toy/children’s superstore), and demographic-specific markets (e.g. luxury condos, discount supermarket or club, senior adult housing) (Institute of Transportation Engineers 2012). Data are segmented into presumably mutually exclusive categories—each observation may fall within only one land-use category. The process for determining pooling or segmenting land-use categories is seemingly ad hoc, classifying data based on the economic industry for the type of product or service provided. There exists no clear public record, to the best of the

author's knowledge, of how these land-use categories were originally or are currently determined.<sup>9,10</sup>

As discussed previously, in this manuscript, we focus on retail and service land uses—both generally observed in “commercial” zoning categories in practice. But “commercial” land uses would also generally include rates provided for services rendered in other building types (such as offices). They are not included in this category. Businesses located in offices that vary across the types of services they provide (e.g., engineering, architectural, legal) are generally lumped together into general office categories—with the exception of medical services offices, which are lumped together in a separate land use. Conversely, retail and retail-like services are not generalized by the structure type in the same way. They are segmented into categories—at varying levels of detail—mostly comparable to the detailed economic industry classifications described in the hierarchical North American Industry Classification System (NAICS) taxonomy.

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<sup>9</sup> Members of the Institute of Transportation Engineers technical board who are known contributors to the current and previous *Trip Generation Handbooks* were contacted for potential references and background information in October 2015 and again in March 2017. The author has not yet gotten a response (July 20, 2017).

<sup>10</sup> It is likely that the methods for testing the differences (or similarities) include a combination of professional judgement and statistical tests assuming normally distributed data, as used for testing the changes in trip rates over time (Institute of Transportation Engineers 2014, 7).

More recently developed methods have produced generalized land use categories, relying upon small datasets spread across a wider range of urban contexts. The result has been a much aggregate categorization compared with ITE's taxonomy: residential (sometimes multifamily versus single-family), commercial or occasionally retail and service (sometimes restaurant), and recreation (Currans and Clifton 2015; Ewing et al. 2011; Millard-Ball 2015). In these more recent improvements to methodologies, the authors have suggested or required the data used for their adjustments be segmented in much broader categories, avoiding too much specificity that would limit overall power and applicability while attempting to capture behavior as it varies from location to location (Clifton, Currans, and Muhs 2013; Millard-Ball 2015; Shoup 2003).

### *Defining Land Use*

Defining land use is no small task—and providing a consistent definition to apply across jurisdictions with varying regional planning goals, needs, concentration areas, objectives, and problems only further complicates this process. The American Planning Association (APA) released the Land Based Classification Standards (LBCS) in an attempt to do just that. A multidimensional system defined originally by Guttenberg in (1959), and then again in (1984) and (2002)—the process of defining something so quick to evolve is a dynamic process. Guttenberg (2002, 1959) argued that a consistent classification system requires multiple dimensions to accurately and consistently describe land use that is adequately sensitive to a range of planning objectives and arenas. The dimensions from this work included definitions for:

- Ownership: the relationship between the land rights and use;

- Site: describing the structures and developed state of the land;
- Structure: indicating that the type of building and potential use, may differentiate between the relationship between the structure and larger regional special structure (e.g., superstore, regional center);
- Economic function: the economic industry function; and
- Activity: descriptions of what people do at each use.

Ultimately, the system was developed with the ability to add dimensions—extending evaluative descriptions with prescriptive (Guttenberg 1984) or allowing for subclassifications such as “activity level,” “time pattern,” or “regional versus local generators” (Guttenberg 1959).

Generally, the ownership and site dimensions are generally irrelevant during TIA estimation. However, ownership of the land/building (e.g., rent, own) may indicate who is developing the land and how much information is known about the occupying entity. Nearly all trip rates describe travel to and from structures, with the exception of recreational parks and land uses with acre-based indicators. This leaves most of ITE’s definitions to fall within two dimensions: economic function and activity. While defining “activity” may be closest to linking behavior with “activity levels”, ITE’s definitions tie most closely with economic function—with the exception of a few aspects included in definitions (e.g., drive through, centers, superstores) that more accurately reflect structure or activity.

### ***ITE's Trip Generation Handbook Data***

Although ITE generously supported access to the data through the OTISS software,<sup>11</sup> these data were generally provided in graphic form. Data were queried—for each land-use category, time period, and independent variable, year of data collection, and region—and individual observations (trip counts) were digitized. Although ITE notes the data included in the 9<sup>th</sup> edition *Manual* (2012) to be collected between 1960 and 2013, a small percentage of data were identified as being much older than that. Data were also queried by the region of the data collection (e.g., Central, Pacific, Eastern, or Midwest); any observations that did not have a region and a year associated with it were removed for analysis.<sup>12</sup>

These data were not without limitations. Through filtering and querying to compile the data set, the digitizing of the graphics would likely result in the introduction of additional measurement error. For any one data collection, a single observation (counts) may also correspond with more than one independent variable; a restaurant, for

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<sup>11</sup> The Online Traffic Impact Study Software (OTISS, accessible at: [otisstraffic.com](http://otisstraffic.com)) is a product from a third-party company that provides alternative online filtering and querying tools to search ITE's *Trip Generation Handbook* trip generation rates. They purchase a license from ITE to use its data and additional ability to filter data by age and region. These variables are not accessible through ITE's *Handbook*, which is only provided in hardcopy format.

<sup>12</sup> Although no contextual information beyond the region of data collection was provided, the authors determined that without the date and location (no matter to what degree masked), the trip rates were just numbers without any context at all and therefore should not be included in this analysis.

examples, may be observed once but included as a rate per square footage, per employee, and per seat. For this analysis, we consider only those provided for rates measured by the square footage of the land use. In Figure 3-1, the distribution of vehicle-trip rates (lower x-axis, black box plots and red dots) and the range of the age (upper x-axis, blue bar) are plotted for each category.

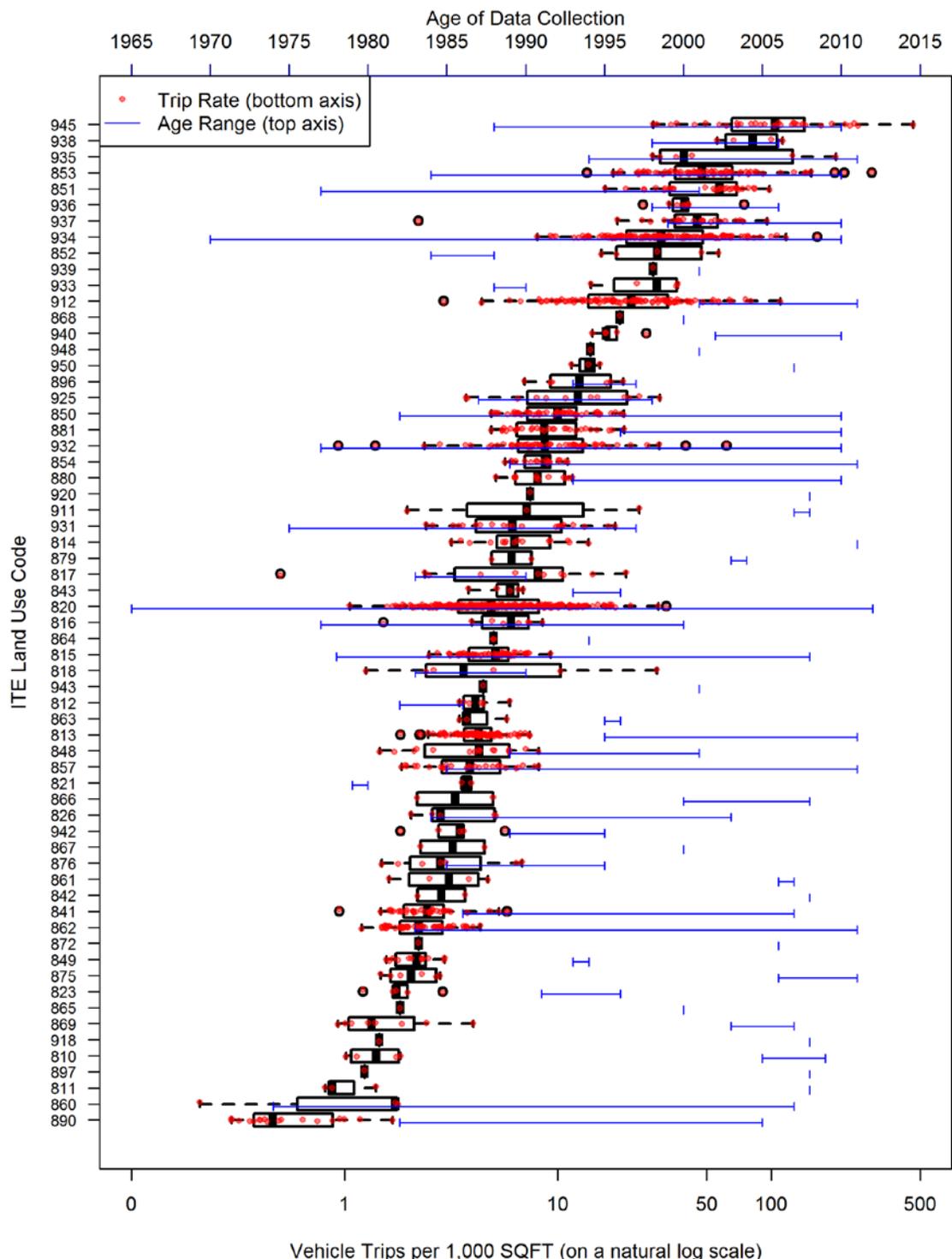


Figure 3-1 Boxplot of Trip Rate (bottom x-axis, black whiskers and red dots) and Age (top x-axis, blue whiskers) for Retail and Service Categories (y-axis)

***How representative are these data of retail and service land use exhibited in the US?***

With more than 170 land uses total, ITE's *Handbook* provides a wide variety of detailed land-use categories. The ability to discuss how these land-use categories are representative of the universe of land use in the US provides several benefits. First, representative data allows for more strategic and efficient sampling. If existing data represent an adequate variety of contexts (built environment, regions, demographics) within a given land use, one might direct funds to data collection of land uses that are underrepresented in the data. The estimated costs associated with keeping up the existing land-use taxonomy are considered in the results—comparing expenses with the relative benefits of a detailed taxonomy. Second, a representative data set (or a data set where the representation is explicit) is more readily aggregated into pooled rates—a common complaint from agencies and practitioners who struggle to pin down the detailed land use codes early in the development review process.

To compare the distribution of ITE's retail and service data, we compare with the distribution of retail and service businesses in one regional area, Portland, Oregon for investigation and evaluation. First, a crosswalk is developed to connect ITE's land-use categories and the 2007 North American Industry Classification Standards (see Table 3-1 and Table 3-2). Then, ITE's data are aggregated into a simplified table—pooling some similar land-use categories for simplicity (see Table 3-3, left). Lastly, using the 2010 Environmental Systems Research Institute (ESRI) Business Analysis data set for the Portland, Oregon area, establishments are pooled into comparable land-use categories (see Table 3-3, right). Note that some classifications have more than one land-use

category (LUC), even then a generalized examination of how land use is represented in this dataset as a whole.

**Table 3-1 ITE's 9<sup>th</sup> Edition *Handbook* (2014) Retail and Service Land-use categories Crosswalk with the 2007 North American Industry Classification System (NAICS) Codes (1 of 2)**

Land Use Code	Category	Land Use Name	2007 NAICS Code	Descriptive Used in Models <sup>13</sup>
810	Retail	Tractor Supply Store	42382	H,G
811	Retail	Construction Equipment Rental Store	532412	H,G
812	Retail	Building Materials and Lumber Store	4441	H,G
813	Retail	Free-Standing Discount Superstore	452111	G,S
814	Retail	Variety Store	45299	G
815	Retail	Free-Standing Discount Store	452111	G
816	Retail	Hardware/Paint Store	4441	G
817	Retail	Nursery (Garden Center)	44422	H,G
818	Retail	Nursery (Wholesale)	44422	H,G
820	Retail	Shopping Center	452111	G
821	Retail	Shopping Center - Christmas Time	452111	G
823	Retail	Factory Outlet Center	452111	G
826	Retail	Specialty Retail Center	452111	G
841	Retail	Automobile Sales	4411	H,G
842	Retail	Recreational Vehicle Sales	44121	H,G
843	Retail	Automobile Parts Sales	44131	G
848	Retail	Tire Store	44132	H,G
849	Retail	Tire Superstore	44132	H,G,S
850	Retail	Supermarket	44511	G
851	Retail	Convenience Market (Open 24 Hours)	44512	C
852	Retail	Convenience Market (Open 16 Hours)	44512	C
853	Retail	Convenience Market with Gasoline Pumps	44711	C
854	Retail	Discount Supermarket	44511	G
857	Retail	Discount Club	45291	H,G
860	Retail	Wholesale Market	45291	H,G
861	Retail	Sporting Goods Superstore	45111	G,S
862	Retail	Home Improvement Superstore	44411	H,G,S
863	Retail	Electronics Superstore	443	G,S
864	Retail	Toy/Children's Superstore	45112	G,S
865	Retail	Baby Superstore	45112	G,S

<sup>13</sup> **Notes:** **C:** Convenience or high generator dummy; **H:** Heavy goods dummy; **G:** Goods dummy; **S:** Superstore dummy; **D:** Drive-through dummy; **R:** Restaurant dummy; **N:** Not included in manuscript analysis of square footage, data mostly provided with independent variable "bays".

**Table 3-2 ITE's 9<sup>th</sup> Edition Handbook (2014) Retail and Service Land-use categories Compared with the 2017 North American Industry Classification System (NAICS) Codes (2 of 2)**

Land Use Code	Category	Land Use Name	2007 NAICS Code	Descriptive Used in Models
866	Retail	Pet Supply Superstore	45391	G,S
867	Retail	Office Supply Superstore	45321	G,S
868	Retail	Book Superstore	451211	G,S
869	Retail	Discount Home Furnishing Superstore	4422	H,G,S
872	Retail	Bed and Linen Superstore	812331	G,S
875	Retail	Department Store	45211	G
876	Retail	Apparel Store	448	G
879	Retail	Arts-and-Crafts Store	45113	G
880	Retail	Pharmacy/Drugstore without Drive-Through Window	44611	D
881	Retail	Pharmacy/Drugstore with Drive-Through Window	44611	D
890	Retail	Furniture Store	4421	H,G
896	Retail	DVD/Video Rental Store	53223	
897	Retail	Medical Equipment Store	42345	H,G
911	Services	Walk-in Bank	522	
912	Services	Drive-in Bank	522	C,D
918	Services	Hair Salon	81211	
920	Services	Copy, Print and Express Ship Store	5614	G
925	Services	Drinking Place	7224	R
931	Services	Quality Restaurant	7221	R
932	Services	High-Turnover (Sit-Down) Restaurant	7222	R
933	Services	Fast-Food Restaurant without Drive-Through Window	7222	C,D,R
934	Services	Fast-Food Restaurant with Drive-Through Window	7222	C,D,R
935	Services	Fast-Food Restaurant with Drive-Through Window and No Indoor Seating	7222	C,D,R
936	Services	Coffee/Donut Shop without Drive-Through Window	7222	C,D,R
937	Services	Coffee/Donut Shop with Drive-Through Window	7222	C,D,R
938	Services	Coffee/Donut Shop with Drive-Through Window and No Indoor Seating	7222	C,D,R
939	Services	Bread/Donut/Bagel Shop without Drive-Through Window	7222	C,D,R
940	Services	Bread/Donut/Bagel Shop with Drive-Through Window	7222	C,D,R
941	Services	Quick Lubrication Vehicle Shop	811191	N
942	Services	Automobile Care Center	8111	
943	Services	Automobile Parts and Service Center	8111	
944	Services	Gasoline/Service Station	4471	N
945	Services	Gasoline/Service Station with Convenience Market	44711	C
946	Services	Gasoline/Service Station with Convenience Market and Car Wash	44711	N
947	Services	Self-Service Car Wash	811192	N
948	Services	Automated Car Wash	811192	
950	Services	Truck Stop	447	

For some of ITE's land uses, the sample size is relatively high (Shopping Center, LUC 820, N=288). For others, it is very low (Hair Salon, LUC 918, N=1). Wholesale trades is generally underrepresented in ITE's data, compared with what is observed in Portland, Oregon (15% versus 3% for land-use categories and <1% in observations, respectively), as are land uses that fall under "Repair and Maintenance" and "Personal and Laundry Services" (21% versus 10% and 1%). Meanwhile, retail land uses are overrepresented (26% versus 37% and 33%).

It would benefit the user of these data to explore how these baseline suburban data are representative of different contexts and establishments of different sizes. ITE's data represents mostly suburban land uses, as the institute reminds us in the *Handbook* (2014). Is this data consistent with similar economic industries across contexts? Are these data representative of the size of each land use (e.g., square footage, average number of employees)? One is not able to answer these questions with the given data as all location information is masked.

**Table 3-3 Distribution of Retail and Service Land Uses and Observations as Provided in ITE's 9<sup>th</sup> Edition (2014), Compared with Counts of Firms by Industry in Portland, Oregon**

2007 North American Industry Classification System (NAICS) Codes <sup>2</sup>	ITE 9th Edition <i>Handbook</i>				ESRI 2010 Business Analyst (Firms)	
	Counts <sup>1</sup>		Proportion (%)		Counts	%
	LUC	Obs	LUC	Obs		
<b>Wholesale Trade (42)</b>	<b>2</b>	<b>5</b>	<b>3%</b>	<b>0%</b>	<b>3,790</b>	<b>15%</b>
Merchant Wholesalers, Durable Goods	2	5	1%	0%	2,897	11%
Merchant Wholesalers, Nondurable Goods	0	0	0%	0%	893	3%
<b>Retail Trade (44)</b>	<b>25</b>	<b>437</b>	<b>37%</b>	<b>33%</b>	<b>6,683</b>	<b>26%</b>
Motor Vehicle and Parts Dealers	5	71	7%	5%	1,048	4%
Furniture and Home Furnishings Stores	2	26	3%	2%	646	3%
Electronics and Appliance Stores	1	3	1%	0%	735	3%
Building Material and Garden Equipment and Supplies Dealers	5	82	7%	6%	1,009	4%
Food and Beverage Stores	4	103	6%	8%	1,261	5%
Health and Personal Care Stores	2	41	3%	3%	603	2%
Gasoline Stations	5	104	7%	8%	276	4%
Clothing and Clothing Accessories Stores	1	7	1%	1%	1,105	4%
<b>Retail Trade (45)</b>	<b>17</b>	<b>505</b>	<b>25%</b>	<b>38%</b>	<b>2,997</b>	<b>12%</b>
Sporting Goods, Hobby, Book, and Music Stores	5	10	7%	1%	827	3%
General Merchandise Stores	10	491	15%	37%	314	1%
Miscellaneous Store Retailers	2	4	3%	0%	1,720	7%
Nonstore Retailers	0	0	0%	0%	136	1%
<b>Finance and Insurance (52)</b>	<b>2</b>	<b>102</b>	<b>3%</b>	<b>8%</b>	<b>1,400</b>	<b>5%</b>
Credit Intermediation and Related Activities	2	102	3%	8%	1,400	5%
<b>Real Estate and Rental and Leasing (53)</b>	<b>2</b>	<b>9</b>	<b>3%</b>	<b>3%</b>	<b>528</b>	<b>2%</b>
Rental and Leasing Services	2	9	1%	1%	528	2%
<b>Administrative and Support and Waste Management and Remediation Services (56)</b>	<b>1</b>	<b>1</b>	<b>1%</b>	<b>0%</b>	<b>357</b>	<b>1%</b>
Business Support Services	1	1	1%	0%	357	1%
<b>Accommodation and Food Services (72)</b>	<b>11</b>	<b>274</b>	<b>16%</b>	<b>20%</b>	<b>4,496</b>	<b>18%</b>
Food Services and Drinking Places	11	274	16%	20%	4,496	18%
<b>Other Services (except Public Administration) (81)</b>	<b>7</b>	<b>9</b>	<b>10%</b>	<b>1%</b>	<b>5,273</b>	<b>21%</b>
Repair and Maintenance	5	7	7%	1%	2,244	9%
Personal and Laundry Services	2	2	3%	0%	3,029	12%
<b>Total</b>	<b>67</b>	<b>1,342</b>	<b>100%</b>	<b>100%</b>	<b>25,524</b>	<b>100%</b>

<sup>1</sup> These data represent the most common independent variable (square footage of gross leasable or gross floor area) and time period (PM peak hour of the adjacent street traffic).

<sup>2</sup> Land use codes (LUC) provided by ITE are aggregated into corresponding NAICS classifications which are shown in 2-digit and 3-digit classifications, with the exception of the category 5614.

## Methods

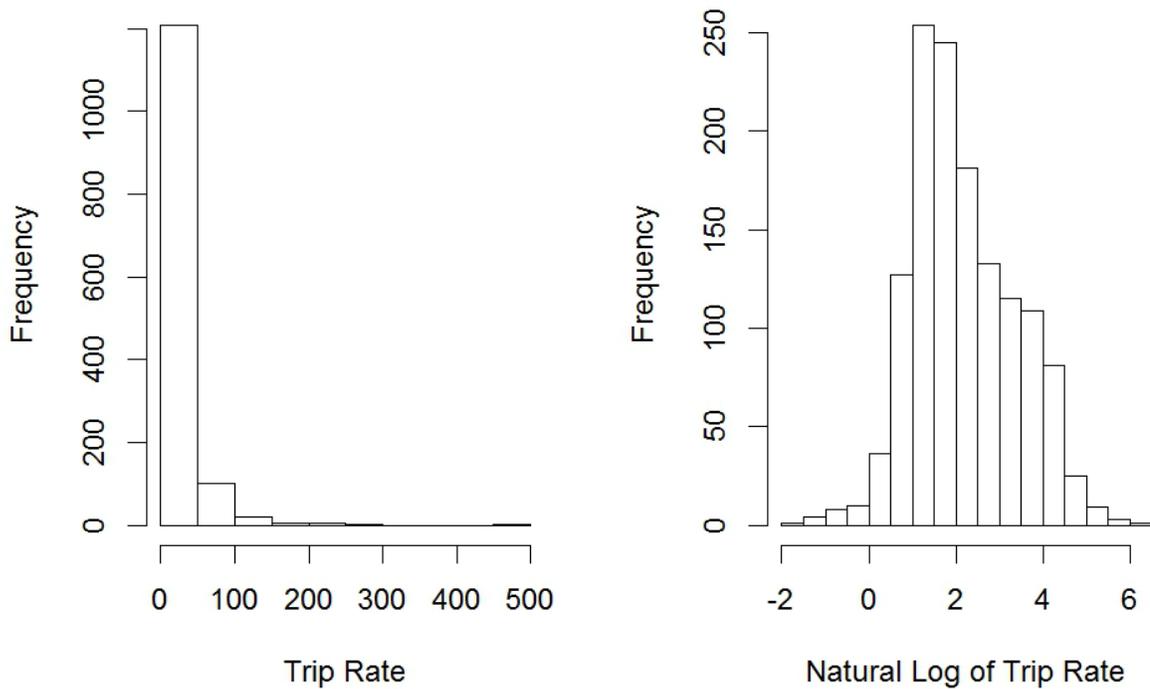
This portion of the study has two subsections describing the two related analyses. First, we explore the relationship between the age of the data and trip rates. Second, we consider the variation explained by ITE's land-use taxonomy, versus a more parsimonious approach.

To examine variation of the trip rates (counts per unit of independent variable) across age or land-use category, we must take into account the count-based nature of these data. For both the analyses of age and land-use categories, we transform vehicle-trip rates using a natural log transformation (see Figure 3-2). The specifics of each analysis can be found in the following subsections.

There are 14 independent variables provided across the 67 land-use categories—although not every land-use category includes every independent variable. There are also nine time periods. The distribution of observations for retail and service land uses across these variables and time periods is provided in Table 3-4. For simplicity, this analysis examines the vehicle-trip counts observed during the PM peak hour of the adjacent street traffic (generally, 4:00 PM through 6:00 PM), for observations measured by the square footage of gross leasable or gross floor area (see shaded values in Table 3-4)<sup>14</sup>.

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<sup>14</sup> Differences of Gross Floor Area (GFA), Gross Leasable Area (GLA), and Occupied Gross Leasable Area (OGLA) are subtle (Institute of Transportation Engineers 2014, 134). GFA includes the



**Figure 3-2 Frequency Distribution of ITE's *Handbook* (2014) Retail and Service for (left) untransformed and (right) transformed using natural log (vehicle-trip counts per 1,000 square footage, PM peak hour of the adjacent facility)**

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sum of all areas of the building, while GLA is defined as the sum of all areas designated for tenant occupancy. GFA is equal to GLA except where open atriums or enclosed malls are included. Neither definition includes garage-parking areas. It is unknown if observations provided under GFA have atriums or enclosed malls. Most observations that use “gross leasable area” include shopping centers, LUC 820 and 821—typical rates (N=288) and rates during Christmas (N=5), respectively—as well as specialty retail center, LUC 826. Only one land use considered “occupied leasable area,” LUC 942, automobile care center. By measuring the “leasable” or “occupied leasable” area, shared space is ignored, deflating the trip rate.

**Table 3-4 Observations of Vehicle-trip counts from ITE's *Handbook* (2014) by Independent Variable and Periods**

Independent Variables:	Time Periods								
	Daily	Weekday				Saturday		Sunday	
		AM Gen.	PM Gen.	AM Adj. Street	PM Adj. Street	Daily	Gen	Daily	Gen
KSF Gross Floor Area	333	522	572	624	1042	199	429	149	125
KSF Gross Leasable Area	170	4	3	87	295	102	89	71	36
KSF Occupied Gross Leasable Area	0	5	5	5	5	1	0	1	0
Acres	15	23	23	23	24	23	23	22	22
Drive-In Lanes	2	19	26	18	85	0	26	0	0
Employees	57	69	69	61	90	62	52	57	49
Seats	24	30	44	35	63	24	27	24	17
Service Bays	12	15	15	20	21	12	14	0	0
Service Stalls Servicing	0	1	1	1	1	1	0	1	0
Positions	1	1	6	1	6	1	1	1	1
Vehicle Fueling Positions	10	65	83	71	112	3	7	3	0
Wash Stalls	1	1	1	0	9	1	3	0	0
AM Peak-hour Traffic on Adjacent Street <sup>15</sup>	0	0	0	42	0	0	0	0	0
PM Peak-hour Traffic on Adjacent Street <sup>15</sup>	0	0	0	0	51	0	0	0	0

Notes: Shaded area indicates the data selected for analysis. Gen: Generator; KSF: 1,000 square feet. Daily: 24-hour counts. Generator: Peak hour of the generator, highest hour of the daily/time period. AM, Adj Street: AM peak hour of the adjacent street traffic (Generally, 7:00 AM to 9:00 AM). PM, Adj. Street: PM, peak hour of the adjacent street traffic (Generally, 4:00 PM to 6:00 PM).

<sup>15</sup> These independent variables (IV) include the "highest hourly volumes of traffic" during the given peak hour. They include the following land-use categories: 853, 854, 934, 937, 944, 945. When examining the relationship between counts and peak-hour traffic flow (linear regression with constant), these IVs are only significantly related for the land use 944 (Gasoline/Service Station).

*Do rates vary by age of the data?*

In the first analysis, we test the relationship between the age of the data and the trip rate, hypothesizing that the trip rates do vary significantly with age. ITE's *Handbook* notes several statistical tests used to examine and compare new and old data as submitted ("combinations of variation from averages, standard deviation expansion, clustering of recent data,  $R^2$ , T-tests, and F-ratios" (2014, 7)). Only the outcomes of "banking industry land uses" age test—walk-in bank (LUC 911) and drive-in bank (912)—were reported; all pre-2000 data for either land uses were removed from the active database. Without further explanation, it is assumed that all tests were conducted with untransformed trip rates, which are likely to have non-normal distributions. The tests conducted in this analysis examine the relationship between age of data and trip rates, transformed into a normally distributed variable.

To control for the potential variation in trip rates across land-use categories, we consider only categories that have 50 observations or more, including: Free-Standing Discount Superstore; Free-Standing Discount Store; Shopping Center; Convenience Market with Gasoline Pumps; Home Improvement Superstores; Drive-in Banks; High-Turnover (Sit-Down) Restaurant; Fast-Food Restaurant with Drive-Through Windows. For each land use, a single regression was estimated—regressing the transformed trip rate upon the independent variable and the age, described numerically here:

$$\ln\left(\frac{trips}{KSF}\right) = \beta_{KSF} * KSF + \beta_{AGE} * AGE + \varepsilon,$$

where: *trips* are the observed vehicle-trip count; *KSF* is ITE's independent variable 1,000 square feet of gross floor or leasable area; and  $\ln(\textit{trips}/\textit{KSF})$  is the natural log transformation of the vehicle-trip rate (*trips/KSF*). The age of the data, *AGE*, is measured in years since 2017 and was computed using the year of data collection, as provided in OTISS. The estimated parameters— $\beta_{KSF}$  and  $\beta_{AGE}$ —are the estimated coefficients that represent the relationship between the square footage (*KSF*) and the age of the data (*AGE*) with the transformed trip rate, respectively.

The elasticity describing the relationship between trip rates and age were then computed, considering the log-linear regression specification, as described here:

$$\eta = \beta_{AGE} * \overline{AGE}.$$

***Do rates vary across land-use categories?***

The second analysis examines the contribution of ITE's land-use taxonomy to explaining variance in trip rates, compared with an aggregated categorization. The simplified categorization segments land uses into those that provide: (C) convenience/high-turnover services;<sup>16</sup> retail that includes (H) heavy goods; and all other land uses. Additional land use characteristics were considered, but excluded due to (a) high correlation with the main dummy variables, or (b) did not provide substantial improvement in the explanation of variance. These characteristics include:

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<sup>16</sup> The convenience/high-turnover category was also negatively correlated with the size of the establishment.

general goods or retail that may require a bag to carry goods; superstore, categories in which the description was listed as a “superstore”;<sup>17</sup> drive through, categories in which the description denotes a drive through; and restaurants, any land use that includes the selling of prepared food. All categorization considered (listed and denoted in Table 3-1 and Table 3-2) represents a simplification to the ITE taxonomy, which includes 63 different land-use categories for retail and service uses<sup>18</sup>.

The purpose of this analysis is to examine the contribution of ITE’s extensive retail and service taxonomy and segmentation. Two types of tests were performed on transformed trip rates. First, an analysis of variance was conducted and the intraclass correlation (ICC) was computed. The ICC assesses the “proportion of the total variance of a variable that is accounted for by the clustering (group membership) of the cases” (Cohen et al. 2002, 537)—an indication of how much variance each land use categorization captures. However, these results compare the variation of vehicle-trip rates captured by land use alone in a one-way analysis of variance ANOVA)—without controlling for additional variation in trip rates captured by the size of the

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<sup>17</sup> Not every “superstore” category has a corresponding “non-superstore” category within the same economic function. For example, the taxonomy includes a “Tire Store” and a “Tire Superstore,” but no “Toy/Children’s Store” in comparison to the “Toy/Children’s Superstore.”

<sup>18</sup> ITE’s taxonomy actually includes 67 land uses. However, four of those uses (denoted “N” in Table 3-8) were not included in ITE’s *Handbook* under “square footage.” They are therefore dropped from this analysis.

establishment. Second, a series of ordinary least squares (OLS) regressions were estimated to examine the comparative contribution of (M1) ITE's taxonomy and (M2b) the aggregated taxonomy, compared with the (M0) base case: no land use indicators. The three models can be described mathematically as follows:

$$M0: \ln\left(\frac{trips}{KSF}\right) = \beta_0 + \beta_{KSF} * KSF + \varepsilon$$

$$M1: \ln\left(\frac{trips}{KSF}\right) = \beta_0 + \beta_{KSF} * KSF + \beta_l * Dummy_l + \varepsilon$$

$$M2: \ln\left(\frac{trips}{KSF}\right) = \beta_0 + \beta_{KSF} * KSF + \beta_C * C + \beta_H * H + \varepsilon$$

Where,  $\beta_l$  and  $Dummy_l$  are the estimated coefficient and corresponding dummy indicator for each land-use category,  $l$  in the set of land-use categories  $\{l, N - 1 = 62\}$ .<sup>19</sup> The variables C and H indicate the convenience/high-turnover and heavy goods land uses, respectively. These variables corresponding with their estimated parameters:  $\beta_C$  and  $\beta_H$ . For each of these equations, four metrics are computed to compare the contribution of each land-use taxonomy: (1) Adjusted R<sup>2</sup>, (2) Akaike Information Criterion (AIC), (3) Root Mean Square Error (RMSE), and (4) Normalized Root Mean Square Error (NRMSE).

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<sup>19</sup> One land use dummy indicator is excluded to provide a base case. Estimated coefficients,  $\beta_l$ , are interpreted as the change in transformed trip rate, as it compares to the base case indicator.

## Results

### *Vehicle-trip rates Have Decreased Significantly Over Time*

For all eight land uses observed, the age of the data significantly explained variation in the relationship with the trip rate (see Table 3-5 and Table 3-6).<sup>20</sup> The relationships ranged from elasticities of 0.2 to 2.4% —indicating trip rates could be more or less elastic depending on the land use. Findings from this portion of the analysis should be interpreted with caution—the discussion section provides more context for these results.

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<sup>20</sup> For almost every land use tested, a non-linear component in this relationship was also significant—an indication of diminishing slope describing the relationship between age and trip rate. This is not included in the regressions provided; reasons are discussed in the discussion.

**Table 3-5 Estimating Trip Rate (Natural Log Transformation) by Square Footage and Age, table 1 of 2**

Land Use Code	813 Free-Standing Discount Superstore				815 Free-Standing Discount Store				820 Shopping Center			853 Convenience Market with Gasoline Pumps				
	Coef.	SE	p		Coef.	SE	p		Coef.	SE	p	Coef.	SE	p		
1,000 Square Feet (KSF)	0.01	0.00	0.00	***	0.01	0.00	0.00	***	0.00	0.00	0.00	***	0.48	0.07	0.00	***
Age (Years from 2017)	0.02	0.01	0.00	***	0.03	0.01	0.00	***	0.05	0.00	0.00	***	0.12	0.01	0.00	***
Elasticity of Age Coefficient	0.2				0.6				1.7			2.4				
Observations (N)	86				53				288			69				
Sources (M)	17				19				101			15				
N/M	5.1				2.8				2.9			4.6				
R <sup>2</sup>	0.97				0.95				0.85			0.93				
Adjusted R <sup>2</sup>	0.97				0.95				0.85			0.93				
Residual Std. Error	0.26				0.37				0.68			1.06				
F-Statistic	1257.10				467.80				819.42			452.10				
<b>Summary Statistics: Mean (Standard Deviation) Minimum - Maximum</b>																
Trip Rate (vehicle trips per KSF)	4.3 (1.1) 1.8 - 7.4				5 (1.4) 2.5 - 9.2				6.3 (4.3) 1.1 - 32.3			62.3 (48.9) 13.7 - 296.8				
Age of data	10.4 (4.6) 6 - 22				20.2 (4.5) 9 - 39				32.1 (10.5) 5 - 52			19.7 (8.5) 7 - 33				

**Notes:**

Dependent Variable: Natural log of vehicle trip ends per 1,000 square feet of gross floor or leasable area, PM peak hour of the adjacent street traffic

KSF: 1,000 Square Feet of Gross Floor Area or Leasable Area

Coef: Estimated Coefficient; SE: Standard Error; t: t-statistic; p: p-value

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table 3-6 Estimating Trip Rate (Natural Log Transformation) by Square Footage and Age, table 2 of 2**

Land Use Code	862				912				932				934			
	Home Improvement Superstore				Drive-in Bank				High-Turnover (Sit-Down) Restaurant				Fast-Food Restaurant with Drive-Through Windows			
Variable	Coef.	SE	p		Coef.	SE	p		Coef.	SE	p		Coef.	SE	p	
1,000 Square Feet (KSF)	0.00	0.00	0.00	***	0.18	0.04	0.00	***	0.06	0.04	0.13		0.29	0.06	0.00	***
Age (Years from 2017)	0.03	0.01	0.00	***	0.22	0.02	0.00	***	0.08	0.01	0.00	***	0.09	0.01	0.00	***
Elasticity of Age Coefficient		0.4				2.2				1.5				2.3		
Observations (N)		51				99				58				131		
Sources (M)		9				15				30				31		
N/M		5.7				6.6				1.9				4.2		
R <sup>2</sup>		0.85				0.92				0.77				0.90		
Adjusted R <sup>2</sup>		0.84				0.92				0.76				0.90		
Residual Std. Error		0.36				0.89				1.13				1.09		
F-Statistic		133.35				565.20				93.49				605.13		
<b>Summary Statistics: Mean (Standard Deviation) Minimum - Maximum</b>																
Trip Rate (vehicle trips per KSF)		2.4 (0.8)	1.2 - 4.3			25.8 (17.7)	2.9 - 110.4			11.4 (9.6)	0.9 - 62			37.3 (23.9)	8 - 165	
Age of data		13.3 (5.9)	6 - 34			10 (2.6)	6 - 16			18.1 (8.3)	7 - 40			24.7 (8.4)	7 - 47	

**Notes:**

Dependent Variable: Natural log of vehicle trip ends per 1,000 square feet of gross floor or leasable area, PM peak hour of the adjacent street traffic

KSF: 1,000 Square Feet of Gross Floor Area or Leasable Area

Coef: Estimated Coefficient; SE: Standard Error; t: t-statistic; p: p-value; \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table 3-7 Ordinary Least Squares Regression Analysis Results, table 1 of 2**

<b>Model:</b>	<b>Reference</b>			<b>M0</b>			<b>M2 (a)</b>			<b>M2 (b)</b>		
<b>Specification:</b>	<b>Intercept only</b>			<b>Intercept + KSF</b>			<b>Intercept + KSF + C</b>			<b>Intercept + KSF + C + H</b>		
	<b>Coef.</b>	<b>S.E.</b>	<b>P-value</b>	<b>Coef.</b>	<b>S.E.</b>	<b>p-value</b>	<b>Coef.</b>	<b>S.E.</b>	<b>P-value</b>	<b>Coef.</b>	<b>S.E.</b>	<b>P-value</b>
Constant	2.14	0.06	0.00 ***	2.44	0.06	0.00 ***	1.62	0.06	0.00 ***	1.80	0.06	0.00 ***
KSF				0.00	0.00	0.00 ***	0.00	0.00	0.00 ***	0.00	0.00	0.00 ***
C <sup>1</sup>							1.44	0.08	0.00 ***	1.62	0.08	0.00 ***
H <sup>1</sup>										-0.92	0.10	0.00 ***
Observations	317			317			317			317		
R <sup>2</sup>	0.00			0.23			0.65			0.72		
Adjusted R <sup>2</sup>	0.00			0.23			0.65			0.72		
Residual Std. Error	1.104 (df=316)			0.968 (df=315)			0.653 (df=314)			0.584 (df=313)		
F Statistics				95.971*** (df = 1; 315)			294.613*** (df = 2; 314)			272.637*** (df = 3; 313)		

**Notes:**

\* p-value < 0.1; \*\* p-value < 0.05; \*\*\* p-value < 0.01

Coef: Estimated Coefficient; SE: Standard Error; t: t-statistic; p: p-value

Dependent Variable: Natural Log of Vehicle Trips per 1,000 Square Feet of Gross Floor or Leasable Area

KSF: 1,000 Square Feet of Gross Floor or Leasable Area

LUC: Institute of Transportation Engineers' *Trip Generation Handbook* Land-use categories

C: Convenience or High-Turnover Land Uses (see Table 3-1 and Table 3-2)

H: Heavy Goods Land Uses (see Table 3-1 and Table 3-2)

<sup>1</sup> Dummy Variable

Table 3-8 Ordinary Least Squares Regression Analysis Results, table 2 of 2

Model: M1	Coef.	SE	t	p-value	
Constant	0.66	0.50	1.31	0.19	
KSF	-0.00	0.00	-2.57	0.01	**
LUC <sup>1</sup>	811	-0.64	0.58	-1.12	0.27
	897	-0.43	0.71	-0.61	0.54
	810	-0.23	0.58	-0.40	0.69
	918	-0.28	0.71	-0.40	0.69
	869	-0.12	0.54	-0.23	0.82
	875	0.44	0.71	0.62	0.54
	862	0.27	0.51	0.52	0.61
	841	-0.03	0.71	-0.04	0.97
	842	0.40	0.61	0.65	0.52
	861	0.39	0.61	0.64	0.52
	866	0.15	0.71	0.21	0.84
	857	0.79	0.54	1.46	0.15
	813	0.91	0.50	1.81	0.07 *
	815	0.83	0.58	1.44	0.15
	820	0.84	0.52	1.62	0.11
	814	1.22	0.52	2.37	0.02 **
	911	1.29	0.58	2.24	0.03 **
	920	1.35	0.71	1.92	0.06 *
	880	1.43	0.58	2.48	0.01 **
	854	1.28	0.56	2.29	0.02 **
	932	1.17	0.52	2.27	0.02 **
	881	1.51	0.52	2.88	0.01 ***
	850	1.48	0.52	2.87	0.01 ***
	950	1.97	0.58	3.42	0.00 ***
	940	2.02	0.71	2.86	0.01 ***
	912	2.33	0.50	4.62	0.00 ***
	934	2.50	0.52	4.79	0.00 ***
	937	2.88	0.52	5.58	0.00 ***
	853	2.94	0.51	5.77	0.00 ***
	935	2.86	0.56	5.13	0.00 ***
	945	4.19	0.58	7.28	0.00 ***
Observations	317	Residual Std. Error	0.498 (df=284)		
R2	0.82	F Statistics	39.625*** (df = 32; 284)		
Adjusted R2	0.80				

Notes: See Table 3-7. The basecase for LUC is 860.

### *Little is Gained from Extensive Taxonomy*

In this section, we compare the relative contribution of each taxonomy (ITE versus aggregated) by examining the amount of variation captured by each approach to land use categorization. Due to the findings in the previous subsection—that age is significantly related to the trip rate—only recent data collected is explored in this section (age of less than 10 years). The complete results from the regression analysis in Table 3-7 and Table 3-8. While there is a significant improvement between the aggregated taxonomy and ITE’s taxonomy<sup>21</sup>, it is the extent of this improvement that is evaluated in this section.

Based on the ANOVA analysis, the intraclass correlation (ICC) for the aggregated categorization (two dummies indicating convenience/high-turnover land uses and land uses supplying heavy goods) was approximately 97% that of the ICC for ITE’s taxonomy (see Table 3-9). These results suggest that the aggregated categorization capture nearly all the variation captured by the more detailed taxonomy.

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<sup>21</sup> Extra sum of squares test between nested models M1 and M2b: F-statistic = 5.0 (df: 313, 284); p-value < 0.001.

**Table 3-9 Intraclass Correlation (ICC) Comparing Two ANOVA: ITE's Land-use Taxonomy Versus Aggregated Taxonomy**

<b>Categories</b>	<b>ICC</b>
Aggregated (C and H Dummies, 3 categories total)	0.787
ITE's Taxonomy (32 categories)	0.810

**Notes:**

For ITE's Taxonomy and Aggregated Categories, see Table 3-1 and Table 3-2.

C: Convenience or High-Turnover Land Uses (see Table 3-1 and Table 3-2)

H: Heavy Goods Land Uses (see Table 3-1 and Table 3-2)

The interpretation of results from the OLS regression were similar (see Table 3-10). Comparing the performance of model M1 (ITE's Land-use taxonomy) with M2 (b) (aggregated taxonomy), we observe only a small improvement in the more extensive categorization, compared to the reference (intercept only) model. It is also worth noting that the largest improvement in performance for the aggregated categorization approach resulted from the Convenience/high-turnover dummy (C)—improving the adjusted  $R^2$  and AIC by 0.42 and 248 (respectively) from the baseline M0 model. Comparing the addition of the Heavy goods dummy (H), an additional improvement of only 0.07 in the adjusted  $R^2$  and 71 of AIC respectively compared with only the Convenience dummy (M2 (b) versus M2 (a)). As mentioned previously, other variables were tested and excluded in this section due to limited model improvement or no significance (see Table 3-1 and Table 3-2 to identify these categories).

Depicted graphically, the relationship between the transformed dependent and independent variables (vehicle trips and square footage, respectively) are relatively linear

(see Figure 3-3). The relative difference between convenience land uses and heavy goods is observably higher and lower, respectively.

**Table 3-10 Ordinary Least Squares Regression of Vehicle-trip Rates for (M1) ITE's Land-use taxonomy versus (M2) Aggregated Taxonomy**

Models	Specification	Adjusted R <sup>2</sup>	Alkaike Information Criterion (AIC)	RMSE	NRMSE	Number of Land-use categories
Reference	Intercept	---	966	1.10	0.20	None
M0	Intercept + KSF	0.23	883	0.97	0.17	None
M1	Intercept + KSF + LUC	0.80	491	0.47	0.08	32
M2 (a)	Intercept + KSF + C	0.65	635	0.65	0.12	2 <sup>22</sup>
M2 (b)	Intercept + KSF + C + H	0.72	564	0.58	0.10	3 <sup>22</sup>

**Notes:**

Dependent Variable: Natural Log of Vehicle Trips per 1,000 Square Feet of Gross Floor or Leasable Area

KSF: 1,000 Square Feet of Gross Floor or Leasable Area

LUC: Institute of Transportation Engineers' *Trip Generation Handbook* Land-use categories

C: Convenience or High-Turnover Land Uses (see Table 3-1 and Table 3-2)

H: Heavy Goods Land Uses (see Table 3-1 and Table 3-2)

RMSE: Root Mean Squared Error

NRMSE: Normalized Root Mean Squared Error

While other characteristics may help to explain some additional variation in this relationship of several alternative dummy variables—representing any goods, superstores, drive-through, or restaurants—did not result in substantial improvement in the performance of the model, and often did not result in estimated coefficients indicated as significantly different from zero. That said, there are significant costs associated with extensive segmentation of dataset. Any reasoning or conclusion to adopt complex versus aggregated taxonomies, therefore, should be a decision that weighs the costs with the benefits.

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<sup>22</sup> Number of dummies plus the base case category.

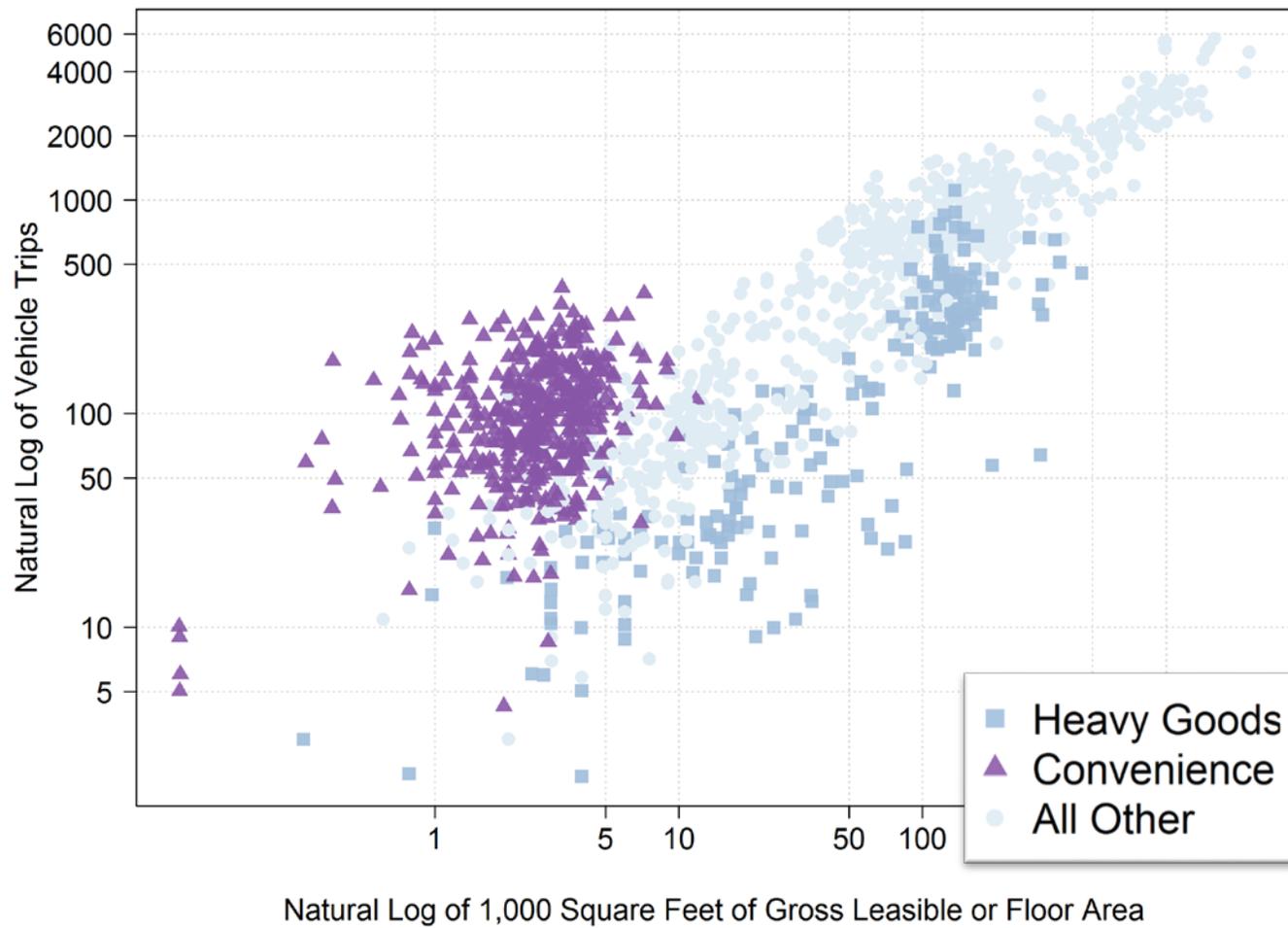


Figure 3-3 Observations for all Retail and Service Land Uses in ITE's 9<sup>th</sup> Edition *Manual* (2012) by Aggregated Taxonomy (PM Peak Hour of the Adjacent Street Traffic, 4:00 PM to 6:00 PM)

### ***The Costs of Segmentation Are High***

Encouraging an overly refined segmentation of data—particularly one that has not been evaluated for performance—has a cost associated with its upkeep. If we require a more adequate sample of 4 observations per category—the sample size required to provide a regression in ITE’s *Handbook* (2014, 23)—and if we were to require data be decommissioned and replaced every 10 years, ITE’s existing taxonomy would require approximately 268 retail and service observations (67 categories). Assuming the cost of each data point ranges between \$8,000 to \$10,000—an estimate derived from two larger studies that collect infill data<sup>23</sup>—the cost of filling gaps in this simplified taxonomy range from USD\$2.1-2.7 million dollars. This cost estimate includes on retail and service land uses during the PM peak hour. Additional time periods would increase these cost estimates (e.g., AM peak or daily counts). Other commercial land uses—such as office building or services typically reserved for office building structures—as well as residential, industrial, warehousing, recreational, ports, would require additional costs.

Additionally, this cost estimate also does not consider the need to control for different urban contexts, which may require additional data collected from place types beyond the suburban data analyzed in this manuscript. Collecting data from multiple place types may increase the costs of data collection three or four times over, as a minimum. Given the slow decline in donated data in the past (see Figure 5-1 in Chapter

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<sup>23</sup> From conversations with Washington, DC Department of Transportation (2015) and estimates derived from Portland State University studies (2012-2017).

5), one might argue that an increased investment in collecting and donating data may be unreasonable, albeit more likely if ITE were to remove the approximate 95% of data that were not collected within the past 10 years (see Figure 5-1).

A call for strategic sampling complicates this cost, but may actually improve the usefulness of data collected. Currently, these data are provided by donation, meaning that the majority of the data<sup>24</sup> are provided by one-off studies, not typically organized or designed in relation to all other studies. This implies that the cost of data collection is placed on the need to collect data in the first place. The estimate for cost per data collection was estimated from larger studies that collected data at dozens of locations within a given region—leveraging the fixed costs of study design and the time it takes to prepare each data collection.

## **Discussion**

Perhaps the most arresting issue uncovered during this analysis is the inability to analyze the representation of these data in more detail. As discussed previously, the masking of location information linked to individual observations—and the inability to link repeated observations provided across multiple time periods or independent variables—inhibits the ability of the analyst to consider the contexts from which these data were collected. In this manuscript, the author explores the representation of retail

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<sup>24</sup> ITE does not currently released information describing who donated the data and how data collection was funded. However, it does provide citations connecting land use data with donated study reports. What proportion of data are provided by each study is indeterminable.

and service land uses in these data sets—comparing the distribution of ITE’s 9<sup>th</sup> edition data (2012) with that within a single region (Portland, Oregon) using the industry classification codes to categorize and compare ITE’s observed data with the proportion of firms. We could not explore: the representation of size of establishments compared with national distributions (Is there a bias toward large establishments?); the correlation with the age of the data and region (Is there a trends of data collections within metropolitan areas across time?); are these data truly representing suburban, single land use, locations with free and unlimited parking and little to no walking, biking, or transit (Are all suburban areas created equal?).

The findings suggest age significantly explains variation in trip rates within the eight retail and service land uses with more than 50 observations. This does not imply causality. It is important to note that the data within each land use were not completely independent. The donated sources for these data provided between 1.9 and 6.6 observations per donation source on average. This significance may be tied to some trend in the way the data were collected nationally over the past six decades. Without context for each observation, it is difficult to say any more about this relationship, and following from this, to adjust or control these rates accordingly. If rates accommodated this observed deflation, are we adjusting for age? Or sampling issues correlated with temporal changes in policies or the demand for these data?

If ITE cannot provide location information, they should provide a better descriptive and quantitative understanding of what these baseline data represent—and guidance on how to control for these differences—particularly for characteristics that

may lead to variation in the observed behavior identified in the literature. That includes, but is not limited to:

- Built environment characteristics, e.g., diversity, density, design measures(Ewing and Cervero 2010);
- Demographics of the surrounding area and the customer base;
- Region, spatial structure, and location within the region;
- Demand management practices;
- Age of the data, and corresponding characteristics, such as the price of gas;
- The date of data collection, and corresponding characteristics, such as temperature or precipitation; and
- Access to, and the cost of, alternative modes.

Provided that the data existing in this database are not too old, post-processing this information can only increase the usefulness and relevancy of these commonly used data. If this information is unable to be found (i.e., if the data are not too old to collect and identify the location- and data collection-specific characteristics), the decision to include these data in applications becomes an ethical one. As ITE notes in their 3<sup>rd</sup> edition *Handbook*, “an example of poor professional judgment is to rely on rules of thumb without understanding or considering their derivation or initial context” (2014, 3). If masking the location information is to remain the standard in practice, the analyst must be able to consider the “initial context” of the data before they attempt to make use of it. Without this context—or the information necessary to understand the context—anyone who applies these data may be guilty of poor professional judgment.

## **Conclusions**

Despite the limitations discussed in the previous section, this manuscript describes two major outcomes, both with implications that may tie directly to practice.

These two outcomes include: (1) older data correspond with significantly higher trip rates; and (2) ITE's extensive land use categorization of retail and services is very expensive with very little statistical improvement over extremely aggregated segmentation.

First, we address the significance of age. While the results point to higher vehicle-trip rates for older data for all eight sufficiently sized land uses datasets, the lack of context for these data limit any ability to understand why this is the case. Overall travel at retail and service land uses may have declined over the years. Or perhaps, newer data may represent more urbanized suburban locations or more multimodal (less automobile-oriented) regions or cultures—which may be inherently related to the demand for data improved or updated data in these locations. Since data are donated, perhaps data were collected purely because developers were expecting lower rates given the location of development? Perhaps data were tied to new trends in retailing or service that developers believed generated less traffic. Without detailed information about the context of each business and location studied, the relationship between age and vehicle-trip rates is arguably impossible to untangle.

Second, we consider the findings that suggest aggregated land-use categories may provide similar accuracy for substantially less cost. For practice, aggregating these land-use categories into something more manageable may mean aggregated fee or impact schedules. Agencies and developers alike often complain about the complexity of land-use categories—particularly when estimation happens early in the development process. For many agencies, even a small change of use may trigger the reassessment of impacts,

which makes a complex taxonomy less attractive to those who manage permitting. But there is also value in understanding the salient features of land use—the aspects of use that derive a change in observed behavior.

For all stakeholders, understanding land use characteristics that correlate in changing behavior means that data are not unnecessarily segmented for the sake of perceived accuracy. Larger sample sizes may mean that other characteristics or variables that describe the context (e.g., built environment, accessibility, and demographics) identified as relating significantly to changes in behavior may be incorporated.

Additionally, as agencies expand the scope of evaluation to multimodal metrics (e.g., mode share, bicycle or pedestrian level-of-service) with a desire for greater sensitivity for urban planning policy measures (e.g., density, mixed use), there will likely be a need to expand the scope of transportation impact data and methods. Strategically simplifying the taxonomy allows for room to innovate without overwhelming the user.

But perhaps more importantly, even today practice is observing huge shifts in how transportation system users interact with land use and facilities. Huge shifts in the retailing landscape have already resulted in widespread use of telecommerce, for example—some suggesting it to be to blame for the closing many late twentieth-century shopping malls. Furthermore, with the advent of many smart-cities initiatives, being open to alternative forms of data being developed and implemented across many agencies in the US may add more value to existing data, or better yet, more value to existing questions about how and when one evaluates and assesses impact and corresponding mitigations. With the emergence of autonomous or connected vehicle technology—and

the huge uncertainty tied to how and when that technology will take shape—will these data, and our corresponding methods, remain relevant for any number of these potential future scenarios? It seems that greater benefit may be had in developing flexible methods sensitive to policy outcomes (e.g., transportation demand management strategies, location efficiencies, affordable housing subsidies, area-wide impacts, zoning or other land use constraints or mechanisms) than extending the already extensive taxonomy.

**CHAPTER 4 ACCESSIBILITY, INCOME, AND PERSON TRIP GENERATION:  
A MULTI-LEVEL MODEL OF ACTIVITY AT FOOD RETAIL  
ESTABLISHMENTS IN PORTLAND, OREGON**

**Introduction**

When urban land is developed, proposed establishments must undergo a transportation impact analysis (TIA)—where the nearby transportation facilities are evaluated against the increased demand derived from the new development. In many jurisdictions, the data and methods used to evaluate impacts relies upon mostly suburban vehicle-trip rates (Institute of Transportation Engineers 2014). There have been recent efforts to improve the shortcomings and increase the applicability of the data and methods for urban trip generation studies used to understand the transportation impacts of new development. Recommended practice, for example, is encouraging a focus on person trips and multimodal data (Institute of Transportation Engineers 2014; Bochner et al. 2016). These efforts aim to increase the sensitivity of these methods to urban contexts (Clifton, Currans, and Muhs 2013; Ewing et al. 2011), and since data on person trips are not currently available in archived form for a variety of land uses and urban environments, most of the new methodologies are implemented as an interim solution that requires an adjustment of ITE Trip Generation vehicle-trip rates, with few exceptions (District Department of Transportation 2015).

Because of this, a common assumption made when applying ITE's *Trip Generation Handbook* (Institute of Transportation Engineers 2014) in urban settings is that average person-trip rates do not vary within a region. To date, nearly all existing

methods for estimating urban trip generation considers person-trip rates to be constant regardless of location attributes, e.g., (Institute of Transportation Engineers 2014; Ewing et al. 2011; Currans and Clifton 2015; Daisa et al. 2013; Bochner et al. 2011). The method assumes urban form relates only to mode share (and perhaps vehicle occupancy) estimated at a site level. This implies that an establishment in the Central Business District would have the same number of people walking through the door that a similar establishment in the suburbs, exurbs, or rural areas. Bid-rent theory, on the other hand, would suggest that areas with higher land rent prices, due to higher levels of accessibility and proximity to markets more attracted to the given land use, would also generate more person trips and therefore stand to attract a larger number of customers earning more sales, e.g., (Alonso 1964; Des Rosiers, Theriault, and Menetrier 2005; Benjamin, Boyle, and Sirmans 1990). In other words, why would developers pay more if they were not expected to obtain more customers, controlling for the price point of products and size of the establishment? Following this theory, we hypothesize that changes in accessibility to destinations, generators, and markets with varying incomes captured by land value are significantly related to variation in person-trip rates.

There are two major implications of applying the assumption of constant person-trip rates in urban areas. First, the amount of non-automobile person trips generated at establishments in locations with higher accessibilities, or land rents, may be greatly underestimated—leading developers to under-plan and under-pay for high levels of transit, walking or bicycling traffic. Second, a direct mode share adjustment, which reduces a proportion of automobile traffic based on total mode share estimates, may be

under-predicting the amount of automobile traffic due to significantly higher person-trip rates in more urban area-types. This manuscript will attempt to quantify the error in existing urban-focused methods to more accurately understand the influence of existing methods which ignore the principals of urban economics.

At this point, urban context only considers the built environment. The socio-economic effects on trip generation are largely ignored despite the fact that travel behavior theory and research recognize them as fundamental influences on transportation outcomes, e.g., (Mokhtarian and Chen 2004). Among these, income is considered one of the primary drivers of trip making and mode choice (Pas 1984). Although demographics such as income are provided as area-wide distributions from the American Community Survey, it has not been utilized on a widespread basis in transportation impact studies, with a couple of exceptions in vehicle trip estimation (Schneider, Shafizadeh, and Handy 2015) and in estimating aspects of behavior at planned mixed-use developments, such as internal capture and mode share (Ewing et al. 2011).

This manuscript aims to address these two shortcomings: (a) the assumption that person trips do not vary across similarly situated land uses with different accessibility, and (b) the role of socio-economics in trip productions and attractions at the establishment level. To do this, we utilize novel sets of data as a proxy for person trips—transaction records at detailed temporal scales for two food retailing land uses: convenience markets and grocery stores in Portland, Oregon. First, we explore the implications of this common assumption—that person-trip rates do not vary across urban and suburban contexts—and the evidence that suggests it is invalid.

## Background

The basis of this assumption—that person trip generation is independent of urban contexts—lies in the use of vehicle-trip counts to estimate the total number of people visiting a site. With too few observations estimate person trips out right, the recommended guidelines suggest converting the plethora of vehicle trip data into estimates for person trips. The conversion of vehicle trips to person trips is made as follows, modified from the recommended guidelines (Institute of Transportation Engineers 2014):

$$PT_{converted} = \frac{VT_{ITE} * VehOcc_{Assumption}}{AutoMode_{Assumption}}$$

Where  $VT_{ITE}$  are the vehicle-trip counts or rates obtained at standard ITE locations, or the “baseline” sites. The vehicle-trip rate can be calculated by dividing vehicle trips by the size of the establishment (e.g., square footage) to derive the counts per size. The variables  $VehOcc_{Assumption}$  and  $AutoMode_{Assumption}$  are estimates of the average vehicle occupancy and automobile mode share to and from the baseline sites. Many of the data collected and provided by ITE were obtained through donated sources, sometimes decades previously when mode share and vehicle occupancy information were not likely collected. If this information was not provided, ITE recommends that the analyst assume some values that best represent what may have been observed in suburban, single-use contexts with free or unconstrained parking and little to no bicycling, walking, or transit use to and from the site (2014). For example, in this

manuscript we assume 95% automobile mode share and 1.1 people per vehicle for all land uses where this information is not provided.

The analyst applies this converted person-trip rate to urban areas using the following formula, again modified from the recommended guidelines (Institute of Transportation Engineers 2014):

$$VT_{context} = \frac{PT_{converted} * AutoMode_{context}}{VehOcc_{context}}$$

Where the vehicle trip estimates for the development context,  $VT_{context}$ , is estimated using an average mode share and vehicle occupancy rate,  $AutoMode_{context}$  and  $VehOcc_{context}$ , approximated for the development context using alternative models estimated using intercept surveys (Institute of Transportation Engineers 2014) or tools developed from household travel surveys (Currans and Clifton 2015; Ewing et al. 2011). The user can also apply mode shares for other modes to estimate the person-trip rates of trip-makers traveling by alternative modes.

There are two problematic issues that pertain to this process. First, the analyst does not actually know the actual context from which the baseline data were observed. Although ITE recommends only donating data collected from locations that meet these baseline conditions, the masking of location and context limit the analyst's ability to make assumptions that reflect these baseline sites. Second, one assumes the person-trip rate calculated from suburban contexts would reflect a similar and unbiased person-trip rate for the same land uses in urban contexts—that the person trips observed in suburban locations are statistically similar to those observed in urban locations. This leads to the

question: how accurate is this converted estimate of person-trip rates compared with observed data?

To investigate this, we examined data from multiple studies collected for residential and lodging, offices, retail, and service land uses collected from multiple studies (District Department of Transportation 2015; Clifton, Currans, and Muhs 2015; Schneider, Shafizadeh, and Handy 2015; Texas A&M Transportation Institute 2016; Western District ITE Chapter 2017; Fehr & Peers 2015). These data were collected in contexts ranging from suburban to high density urban, some with access to high-quality transit and some without. If the assumption holds—the converted person-trip rates will not be statistically different across contexts—the distribution of difference between the converted estimate and observed rates, taken as a percent of the estimated rates, should be normally distributed around zero.

To compare the accuracy of the estimated person rates, we compute the root mean squared error (RMSE) a measure of the average deviation between the estimated and observed values. The RMSE is defined mathematically as:

$$RMSE = \sqrt{\sum_{i=1}^N (PT_{estimated,i} - PT_{observed,i})^2 / N}$$

Where  $PT_{estimated}$  is the rates of person trips estimated by ITE's converted vehicle-trip rates for every observation,  $i$  within the set of observations totaling  $N$ , and  $PT_{observed}$  is the observed person-trip rate for each observation,  $i$ . The scale of the values on RMSE vary somewhat depending on the range of observed values, so it is sometimes

useful to also compare a normalized version of RMSE (or NRMSE) which can be defined mathematically as follows:

$$NRMSE = \frac{\sum_{i=1}^N (PT_{estimated,i} - PT_{observed,i})^2 / N}{Max(PT_{observed,i}) - Min(PT_{observed,i})}$$

For each of the four land uses, these accuracy measures (RMSE and NRMSE) were computed for AM and PM observations (where available)—the peak-hour rate being defined as the maximum hour of person traffic at establishments during the peak of the adjacent street, most often defined as 7:00 AM to 9:00 AM and 4:00 PM to 6:00 PM. The largest discrepancy between the predicted and actual rates is observed in the retail and service land uses, part of which is controlled for by the normalization of the discrepancy with the range of observed values.

**Table 4-1 Accuracy (RMSE and NRMSE) of ITE's Converted Person-trip rates Compared with Observed**

	AM Peak Hour <sup>5</sup>			PM Peak Hour <sup>5</sup>		
	RMSE	NRMSE	Sample	RMSE	NRMSE	Sample
<b>Residential/Lodging<sup>1</sup></b>	0.098	0.068	58	0.078	0.054	58
<b>Office<sup>2</sup></b>	0.233	0.186	24	0.335	0.173	23
<b>Service<sup>3</sup></b>	---	---	0	2011.876	8.608	58
<b>Retail<sup>4</sup></b>	229.184	7.376	15	579.407	4.731	60

**NOTES:**

<sup>1</sup>ITE Land Use Codes: 220, 230, 222, 223, 232, 310

<sup>2</sup>ITE Land Use Codes: 710

<sup>3</sup>ITE Land Use Codes: 925, 932, 936

<sup>4</sup>ITE Land Use Codes: 850, 890, 880, 816, 851, 869, 820, 867, 530, 522

<sup>5</sup>The peak hour is measured during the peak of the adjacent street traffic, generally 7:00 AM to 9:00 AM and 4:00 PM to 6:00 PM.

What these estimates do not show, however, is the direction of this error. A heavy bias in one direction or the other would mark a tendency to overestimate or underestimate. While the conversion method assumes all contexts produce similar rates

compared with suburban contexts, theories of urban economics would suggest higher person-trip activity at establishments in areas with higher accessibility—or urban contexts (this topic is explored in detail for the remainder of this manuscript). With higher trip rates in urban contexts, we aim to examine the discrepancy of predicted values (compared with observed) such that one identifies how much higher these rates may be compared with the estimated values, as defined below:

$$\textit{Percent Higher Than Estimated} = \frac{PT_{\textit{observed}} - PT_{\textit{estimated}}}{PT_{\textit{estimated}}}$$

This value was computed for each observation and plotted against the size of each establishment or development (see Figure 4-1 and Figure 4-2)—the same as used to estimate ITE’s vehicle and converted person-trip rates. Noticeably, the probability that these estimates under-predict total trip-maker activity is more heavily biased in retail and service land uses—compared with residential/lodging and office uses. While some retail and service estimates over-predict person trips for every observation, the majority severely under estimate person trips. It is likely that these locations in urban areas serve high populations of pedestrians. By converting ITE’s vehicle-trip rates using the standard assumptions, one ignores that the vast majority of these person trips are likely capturing walking trips to and from retail and service in more accessible areas. As some agencies are beginning to require the evaluation of pedestrian facilities during development review (as well as cycling and transit) in the form of multimodal level-of-service measures or person delay, the extreme under estimation of person trips ignores these kinds of trips

which, in urban contexts, likely make up additional pedestrian trips leveraging the higher accessibility.

It is this discrepancy that we explore in this manuscript, specifically at retail locations. First, the literature that may provide guidance or explanations as to why this error exists is examined. Second, study setup is designed by examining the data and methods used to assess this assumption—hourly transactions counts collected at 13 grocery stores and 80 convenience market establishments spread across the Portland, Oregon metropolitan region, aggregated into weekly, daily, and peak-hour transaction count. Lastly, the results are explained and implications discussed in the conclusions.

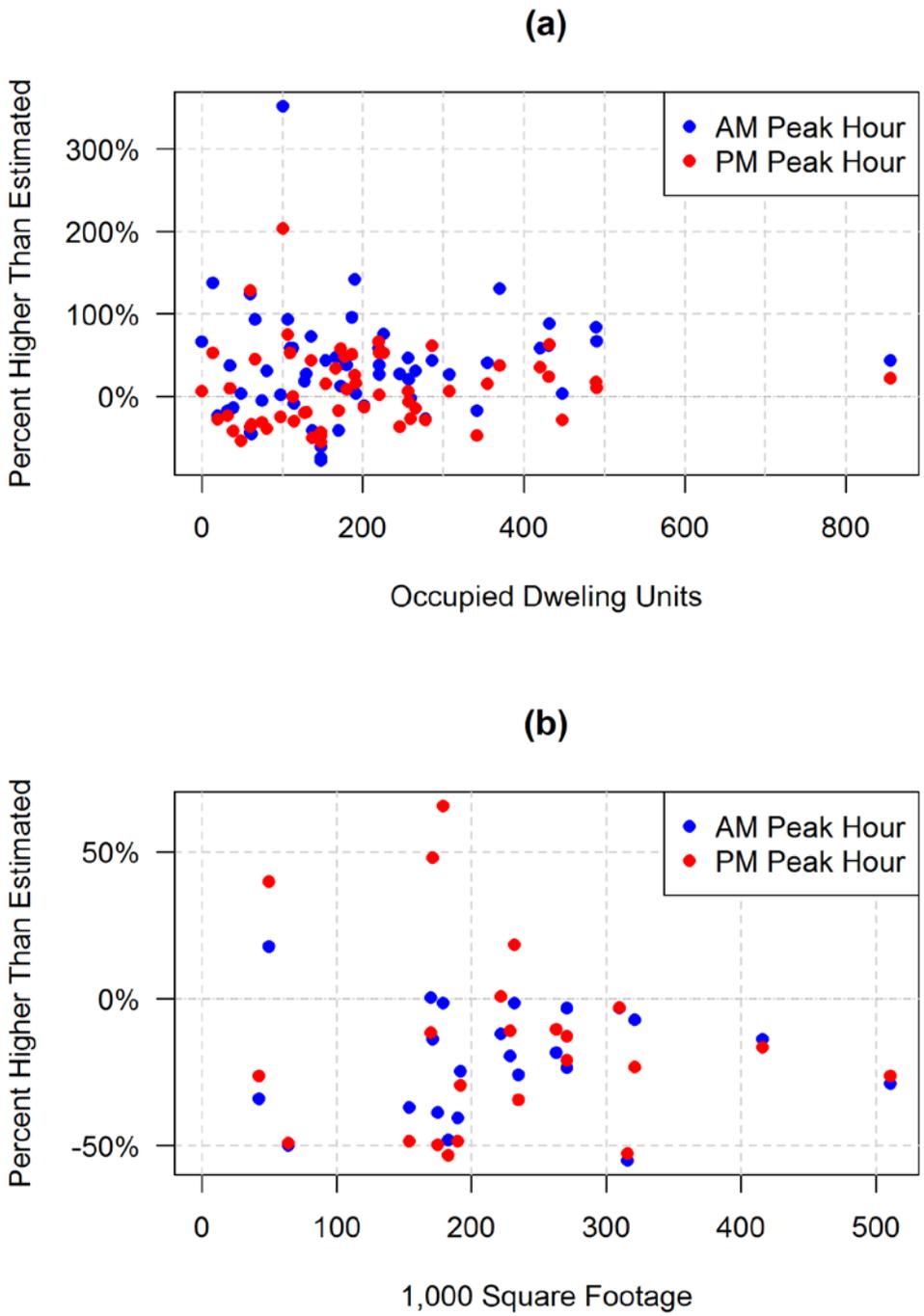
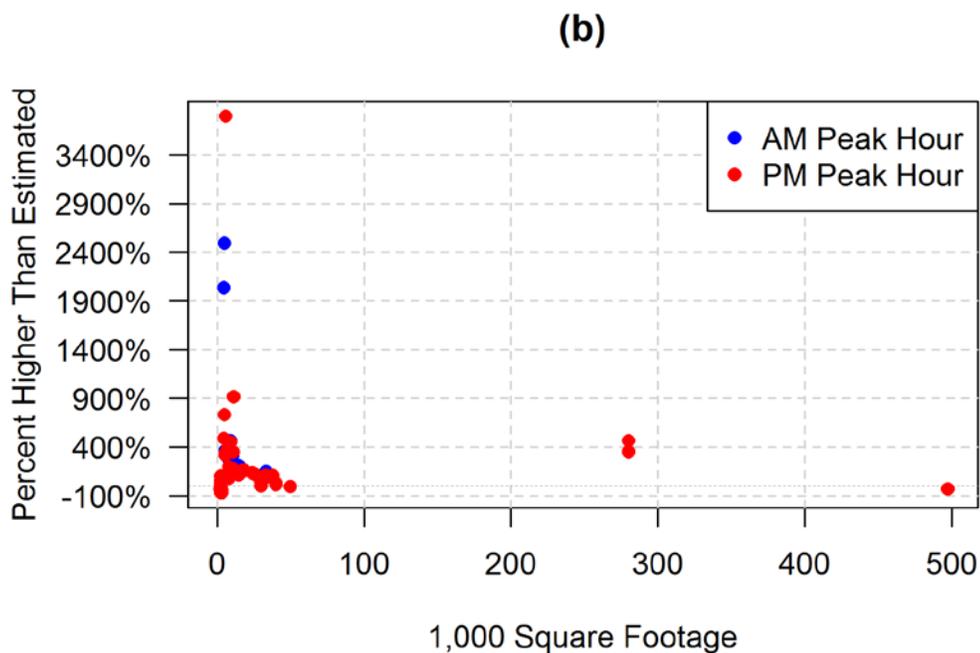
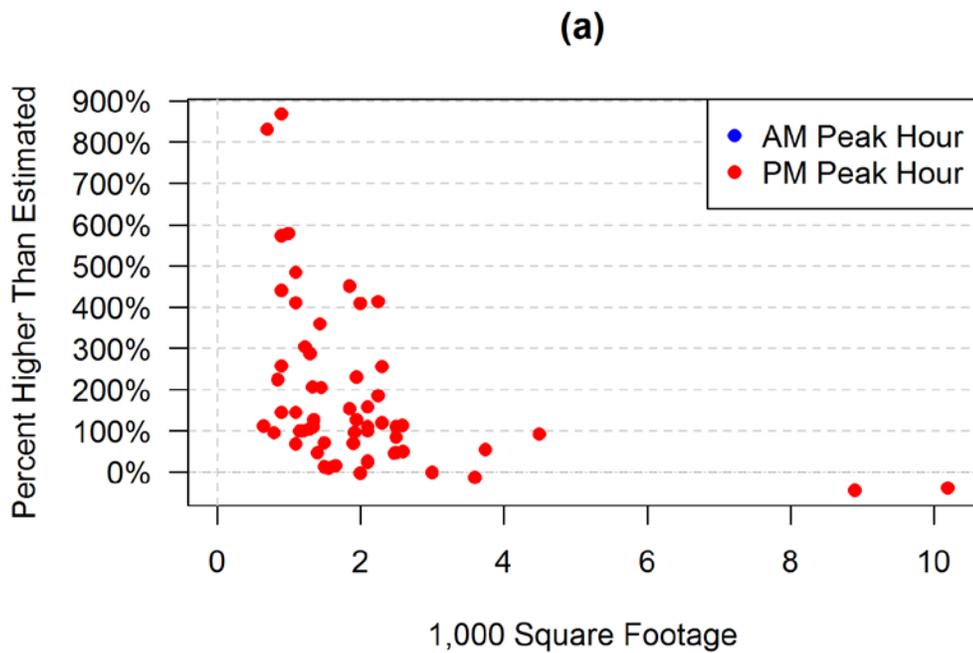


Figure 4-1 How Much Higher are the Observed Person-trip rates Compared to Rates Estimated Using ITE’s Converted Rates: (a) Residential and (b) Office



**Figure 4-2 How Much Higher are the Observed Person-trip rates Compared to Rates Estimated Using ITE's Converted Rates: (a) Service and (b) Retail**

## **Literature**

To examine this question in the literature, three aspects of the literature are investigated: travel-demand modeling and travel behavior; urban economics and spatial structure; and decisions regarding firm location. Within these areas of study, we first explore whether the literature has examined attraction-based person trip generation (focusing on non-household travel activity). We then examine theories of bid rent to establish a basis for this research. Lastly, we examine literature that explores how and why developers locate firms within a region.

### ***Travel-demand modeling and Travel Behavior Literature***

Within the literature of travel-demand modeling, research that has established person trip generation rates at food retailing land uses, particularly those that examine how rates vary across the region were targeted. There are three major limitations of the travel behavior—land use research that allow one to investigate how activity at retail establishments vary across the urban landscape: (a) the limited number of studies focusing on overall person-trip demand or person-trip frequency, (b) the countless efforts focused on defining the built environment and behavior from the trip-maker's household location, and (c) the exclusion of socio-economic information in the definition of urban context. While the aim of this paper is to focus on person trip generation, these limitations extend to aspects of estimating mode shares, trip lengths, vehicle occupancy, ownership and parking.

For the first limitation, we found few other studies have examined the influence of overall person-trip frequency variation, instead emphasizing a mode-specific trip frequency or trip length. Trip frequency and trip rates receive little, if any, attention in travel behavior research, especially at commercial establishments. Studies of person-trip frequency require an examination of the overall derived demand for activities at destinations and the corresponding trips made to reach them, but this is often missing from land use—travel behavior analyses which focus on mode-specific demand (Crane 1996). If trip rates are evaluated, measures are often circumscribed to automobile use in an effort to understand how urban form influences automobile dependence, (Ewing and Cervero 2010), and more recently, attention in this area has ignored trip rates altogether, instead focusing on automobile distance traveled (Ewing and Cervero 2010; M. Boarnet 2011). Without an examination of overall person-trip frequency or demand at commercial establishments, one is left with studies focusing on its mode-based components and the relative influences that relate to an increase or decrease in travel by either walking, biking, automobile, or transit—but rarely evaluated simultaneously, e.g., (Guo, Bhat, and Copperman 2007).

A second limitation is the strong emphasis in research focusing on a household-level unit of analysis that is prominent in nearly all travel behavior research to date. Since much of travel behavior research utilizes household travel surveys, few have investigated the influence from an establishment-based perspective, testing influences of environmental characteristics on travel. Alternatively, some studies focus on household trip frequencies to specific land uses within generally defined areas (Handy 1996). Travel

collected from the household's home-location perspective leaves too few non-work trips observed at any one commercial establishment, preventing any investigation of establishment-based evolution in the variations in terms of trip counts. Fortunately, because these household-based surveys capture travel to various locations across a region, several more recent studies have used these surveys to attach relative differences between changes in behavior in terms of mode choice (Currans and Clifton 2015; Ewing et al. 2011), vehicle occupancy (Ewing et al. 2011), and trip length distributions (Ewing et al. 2011). Although interest recently has arisen in examining the built environment impact at the destination or establishment end of the trip, the emphasis has largely been on local accessibility, such as activity densities or connectivity within a half-mile area (Clifton, Currans, and Muhs 2015; Currans and Clifton 2015; Schneider, Shafizadeh, and Handy 2015).

And third, evidence strongly suggests that socioeconomic influences significantly affect travel behavior, e.g., (Mokhtarian and Chen 2004). However, few trip generation studies have incorporated income or other characteristics of the trip maker or the area surrounding the establishment (Schneider, Shafizadeh, and Handy 2015; Ewing et al. 2011). Yet in regional travel-demand modeling, income—or automobile ownership (as a proxy)—and household size are often the only predictors used to estimate trip generation productions (Martin and McGuckin 1998). Inclusion of this information should be among the improvements being considered to transportation impact studies, but that has only rarely been the case (Schneider, Shafizadeh, and Handy 2015; Ewing et al. 2011).

To understand the variation in site-level activity, one needs to understand the overall demand at attractions such as retail establishments—absent of mode choice. Due to the limitations in the existing travel behavior research investigating overall people trip counts and frequency at commercial establishments, the theories of urban economics and spatial location decisions offer an alternative source for investigation.

***Urban Economics, Spatial Structure, and the Premium Paid for Greater Accessibility***

Theorists in urban economics have long evaluated the spatial structure of urban areas and the location decisions of firms (*e.g.*, 6, 19, 20). For commercial establishments, economic theory (bid-rent theory) assumes that businesses and investors who opt to pay for higher land values in areas with higher accessibilities do so with the expectation that, in return, more customers will have access to their businesses.

Accessibility, as described by Hanson (1959), integrates both the intensity and proximity of destinations reachable from a given location. In terms of characterizing the influence of accessibility on travel behavior, Handy (1992) argued that accessibility can be separated into two components: regional accessibility, defined by longer distances of less frequent trips one has to travel to reach more regionally located shopping centers with a wider range of goods; and local accessibility, defined by the shorter distances or more frequent trips on travels to less-centered, more-ubiquitously spread-out destinations with a smaller range of goods aimed at everyday shopping and convenience.

While several researchers have studied the relationship between residential land value and accessibility (Srour, Kockelman, and Dunn 2002; Kockelman 1998; Iacono and Levinson 2012), it is perhaps more relevant to this study to focus on those that have

investigated the premiums paid by developers and business owners for locating in more accessible areas. Srour et al. (2002) studied commercial land value and found owners paid a premium to locate in areas with higher accessibility to retail and employment destinations, but paid less to live near residents. Although the meaning of the commercial land value analysis was not explicitly addressed in the paper, these findings suggest that there is added value for firms to locate near agglomerations of other commercial establishments and employment centers. Similar to the studies of residential land value, several authors have noted increases in commercial land value near transit stations (Anas 1995; Cervero and Duncan 2002) and business districts (Cervero and Duncan 2002).

These studies established a connection between accessibility, in terms of destinations and proximity, and land value. For commercial properties, this increased land value must be off-set by the rent of businesses locating on the property. Property managers set the rent according to the value of land and the potential success and variability of the business itself (Benjamin, Boyle, and Sirmans 1990). The work by Des Rosiers et al. (2005) separated the influences on shopping center rent into two dimensions: the economic potential of the center's location—a combination of population and corresponding income within the center's vicinity, and; the center attraction of the location—a gravity measure of population accessible to the retail location. The authors found that the economic potential of the location was a major contributor to rent, suggesting businesses pay a premium to locate near high-income residential areas. However, the central attraction of the location (population accessibility) appeared to have

a greater impact in the number of potential customers that came through the door, which in turn relates to higher rents paid.

While these studies lend support for the alternative hypothesis that person-trip rates vary across urban contexts, other aspects of these studies may not translate directly to transportation impact studies. The temporal nature of these urban economic studies extends to quarterly or annual rent data (Des Rosiers, Theriault, and Menetrier 2005), or sometimes to the sale of property (Srouf 2001). At the longest, transportation impact analyses observe a day of traffic, more often a single peak hour supplies the data for analysis. Furthermore, Dunkley et al. (2004) noted a positive and significant relationship between the size of food retail establishments and both density (persons per acre) and median household income. This may suggest that even if higher accessibility to people and income generates more trips, it may not necessarily result in higher levels of activity overall. Finally, management decisions at individual establishments may vary to optimize performance. In the next section, the methods and decisions used to optimize the management of food retailing establishments are explored.

### ***Firm Location Decision-Making***

The decision-making process that a firm uses to decide where to locate an establishment does not occur in a vacuum. As Hernandez et al. (Hernández, Bennison, and Cornelius 1998) revealed, firms have three main levels of location management: strategic, monadic, and tactical. The first occurs at the macro- and meso-level, where larger firms are more concerned with company-wide decisions of location. The monadic level, which may overlap the strategic level, comes to the fore as when the company

focuses on individual stores, as components of a larger network of market bases. At the monadic level, businesses take a micro-management approach. They address the individual markets of each of the establishments, identifying areas where businesses may be modified in name, product or appearance, or expanded (or not) to fit the needs of the nearby market. While larger spatial networking decisions are made at the strategic level, adjustments and refinements are monadic. At the tactical level, a company makes decisions about marketing and product management that reach out to the existing community to address their specific, tailored needs for varying products. At the tactical level, businesses offer loyalty cards or provide location-specific sales, adjusting the supply and demand of products to maximize the transactions for each store.

While the theory of bid-rent suggests that businesses pay a premium for locations that will reward the owner with higher accessibility to customers (and their incomes), the location management from larger firms that organize many establishments in space across markets suggests that businesses also make micro-level decisions to refine the ability to capture their market. While firms locate businesses in a range of environments, they may tailor monadic and tactical decisions to maximize success in locations with less accessibility. If this is the case, variation in foot traffic might cause micro-level monadic or tactical decisions that may wash out benefits of locating in areas with high levels of accessibility to markets, especially in higher-income markets.

Moreover, firms do not always address refined models that identify optimal accessibility when making location decisions. In a follow up survey, Hernández and Bennison (2000) identified nine techniques to assess location decisions, comparing both

the size of the firm (number of outlets) and type of business (type of product), as well as the type of technique(s) used for location decision making while participating in these three levels of location management. The results overwhelmingly show that 96% of businesses rely on experience to reflect decisions made, while 36-55% consider checklist or analogue techniques, 39-42% use cluster analysis, multiple regression, or gravity models, and fewer than 16% consider more technically advanced techniques (e.g., discriminant analysis, neural networks). Of companies that have fewer than 250 outlets—which would include both businesses considered in this study—66% use between 1 to 3 methods, and 25% use 4 to 6. Breaking out by sector, grocery store businesses overwhelmingly use experience as a technique for location decisions (used by more than 75% of companies), but 51 to 74% of grocery businesses used more advanced techniques as well (e.g. Checklists, multiple regression, cluster, and gravity models). The survey results also indicated that all techniques identified were used by at least 25% of the grocery store respondents. While this suggests that the numerous techniques site managers may use to reach their target market customers may vary in complex ways, the timeline of transportation impact studies—often completed before building permits are even issued—may occur long before these managerial decisions are contemplated.

Based on this literature review, we hypothesize that person-trip rates (the overall demand or people through the door) at commercial establishments will be greater at locations for which developers have paid a premium by consciously capitalizing on the benefits of location accessibility (Handy 1996) and proximity to varying income markets (Des Rosiers, Theriault, and Menetrier 2005). These differences, however, may not be

observable at the typical temporal scale of traffic impact analyses, evaluating either daily impacts or those during the peak hour of the generator itself (the establishment) or adjacent street. Because of this, three scales of evaluation will be tested: peak-hour, daily, and weekly transaction rates. The next several sections describe the data, methods and results used to evaluate this hypothesis.

## **Data**

One major problem estimating person-trip rates is that there are so few data available that capture a wide range of local and regional contexts, for a period beyond an hour that allows us to understand the anticipated variation. While there are inherent differences between person-trip counts and transaction counts, which are addressed in the following subsection, the use of transaction data in this study allows us to examine the variation of overall store activity—a proxy for the overall transportation activity, person-trip counts—to determine (a) if (and how much) variation exists, and (b) if so, the location measures that explain this variation. The data for this analysis was donated on request by two local partners—who asked to remain anonymous—providing 24-hour counts over one-to-five, seven-day periods for 84 (24-hour) convenience markets and 13 grocery stores within a single region (Portland, Oregon).

### ***Transaction Data (Dependent Variable)***

As mentioned previously, there are distinct differences between “transaction counts” and “person-trip counts.” A *person-trip count*, as used in ITE’s recommended practice (Institute of Transportation Engineers 2014), is a general term that is often used

interchangeably with the more apt term “*person-trip-end*” count. We use them interchangeably in this manuscript for simplicity. Person-trip counts are defined as the number of people entering or leaving the study development within a given period. If 30 people enter and exit a 2,500-square-foot convenience market within a PM peak hour (5-6 PM, for example), the person trip (end) count is 60 person trips (30 entering and 30 exiting). These counts are often expressed as *person-trip rates* controlling for the size of the development; in the case of convenience markets and grocery stores, this is typically square footage of gross leasable area (GFA) in thousands of square feet (SQFT). For the earlier example, the person-trip rate would be 24-person trip (ends) counts per 1,000 SQFT of GFA.

*Transaction counts*—aggregated by any length of time—reflect the number of sales transactions within each period the business is open. Similar with person-trip rates, *transaction rates* control for the size of each establishment—in this case, for parity, we also use GFA in 1,000 SQFT increments. For this purpose, we use transaction data as a means for understanding relative variation in overall levels of activity, not as a way of estimating overall trip rates. To consider this, one must understand the turnover of activity—the transaction is, after all, at the end of the activity—as well as the relative group size for every transaction estimates. In this initial analysis, we assume that all arrivals occur within the same day and week from which the transaction occurred. As we previously identified that average vehicle occupancy, a proxy for group size of automobile trips, considered at the trip end does not vary across urban context within a region for retail establishments (Currans and Clifton 2015), we assume that this holds for

relative measures of accessibility. The comparison of transaction counts as a proxy to person-trip counts is explored further in Appendix A.

### ***Contextual Characteristics of Developments (Independent Variables)***

As part of our hypothesis, we argue that businesses, particularly retail endeavors, opt to locate in areas with higher levels of accessibility and income—and pay a premium for doing so—so that they may attract higher rates of people walking through the door, particularly when controlling for price point of the goods within the establishment. To examine the variation of transactions across varying levels of accessibility, existing data are used to compute these measures (Table 4-2, and described numerically in Table 4-3). They act as proxy measures for more complex and computationally difficult accessibility measures (Bhat et al. 2001; El-Geneidy and Levinson 2006).

Accessibility itself is broken down into a regional and a local component (Handy 1992). To measure regional accessibility, we examined multiple measures of regional accessibility as defined in the Smart Location Database (SLDB), as well as a more general measure: distance to the central business district (CBD). Although these measures were all highly correlated (Pearson's correlation of +0.96), the Regional Centrality Index considered the relative variation in destinations accessible, weighted by a travel-time decay function. Moreover, because it was calculated for all block groups in the United States, it lends itself well to repeated analyses in external regions. Due to the high correlation, both variables could not be included; instead, we selected the Regional Centrality Index to represent regional accessibility.

For local accessibility—a measure of walkable opportunities, both in terms of alternative destinations and generators of visitors—the gross population and employment density (per acre) at the block group level were measured. Since businesses are paying a premium for more centric, high regionally accessible areas, the average real market value of commercially zoned land per square foot, as well as alternative measures of accessibility correlated highly with activity density (Pearson’s correlation: +0.93). While competition—the number of substitutable businesses—plays a role in attracting higher (or lower) trip rates, the number of similar and potentially substitutable establishments within a ½ mile Euclidean buffer was highly correlated with activity density (Pearson’s correlation: +0.84). The measure of “competition businesses” and “value of commercial land” also corresponded (Pearson’s correlation: +0.88). Comparably, including all variables would introduce multicollinearity issues. Because of this, we select the most simply defined measure—the sum of population and employment densities—to represent local accessibility.

Finally, to account for the accessibility of the establishments to the purchasing market, the area-wide (median) income of the block group of the establishment is considered. Traffic impact analyses—as well as other forms of site-level evaluation (e.g., impact fees, scaling/scoping of the project, rezoning)—are typically completed long before businesses occupy the development, and in many cases, developers intending to lease the space may not know who the tenants will be until long after the fees have been paid and the mitigations negotiated. Furthermore, if the intent of site-level mitigation is to account for travel to the destination in the future, predicting the potential consumer

market of development—sometimes several years before build out—and the corresponding customer behavior is a murky process, at best. Furthermore, do all types of people shop at all types of grocery stores? Likely not. And how can consumer markets be predicted when developers do not yet know the tenants for their commercial developments? This is one of the main limitations of accounting for demographic effects at non-residential or office development. And while this topic is a fruitful area of future analysis and study for transportation impact studies and site-level evaluation, for this manuscript an area-wide measure of median income in the local proximity (census block group of the establishment) is used as a proxy of the demographics of the potential location consumer market.

It is important to note that all locations in this study have free and relatively unconstrained parking at the time of data collection. Additionally, the grocery store and convenience market data were collected in spring and fall, respectively. While there was limited variation in observed temperature, we include a variable to control for total precipitation (inches) during the observation day or week. This measure was computed using historic weather data for the Portland International Airport on the survey day collected online from Weather Underground.

Table 4-2 Description of Accessibility-Related Environmental Measures

Measure	Description	Variables/Source
* Regional Accessibility <i>[index: {0,1}]</i>	Jobs accessible within a 45-minute drive, weighted by a travel time decay function and normalized by the regional total and maximum accessibility value at a block-group level (Regional Centrality Index)	2010 SLDB; Variables: D5cri
* Local Accessibility <i>[people per acre]</i>	Sum of gross population and employment on unprotected land per acre at a block-group level	2010 SLDB; Variables: D1b + D1c
* Median Income <i>[2014 US Dollars]</i>	Median household income at a block-group level	2014 ACS (5-year) Variables: B19013
Distance to the CBD <i>[miles]</i>	Euclidean distance between the establishment address and the center of the central business district (CBD)	Calculated **
Competition <i>[count of establishments]</i>	Number of similar establishments within ½ mile Euclidean distance of the establishment address	2010 ESRI Business Analyst; Variable: NAICS_EXT***
Land Value <i>[2016 US dollars per square foot of land]</i>	Average real market value of land (no building) per square foot for commercial land within a ½ mile Euclidean buffer of the establishment address	2015 RLIS, Tax lot layer; Variables: Landval; Events where Prop_code: 200-292 for Commercial Land

**NOTES:**

CBD: Central business district

SLDB: Smart Location Database - <https://www.epa.gov/smartgrowth/smart-location-mapping#SLD>

RLIS: Regional Land Information System - <http://rlisdiscovery.oregonmetro.gov/>

<sup>1</sup> Used in the subsequent analysis.

\*\* Portland's metropolitan CBD was estimated to be Pioneer Square.

\*\*\* 6-digit NAICS code categories considered include: 445110, supermarkets and other grocery (except convenience) stores; 445120, convenience stores; 445210, meat markets; 445220, fish and seafood markets; 445230, fruit and vegetable markets; 445291, baked goods stores; 445292, confectionery and nut stores; 445299, all other specialty food stores; and 445310, beer, wine, and liquor stores.

*Defining Contextual Groupings for Convenience Markets*

The main caveat of having access to this disaggregate and valuable data were the agreement that the location information (XY-coordinates) had to be partially masked. As part of the data-release agreement, the local convenience market partner in the study asked for groupings of no fewer than five stores to retain the business-sensitive information regarding each individual location. The 84 establishments were divided into 17 groups of four to six based on the location characteristics, as described in this section. Provided with groupings that accommodated the study and the business owner, the local market partner returned the transaction counts data for individual establishments. These counts were categorized according to our predetermined groupings with the individual locations masked. Although the locations for all sites within each group are known, data specific to each location remain confidential. Instead, group averages of variables were calculated to capture variation in our desired location characteristics.

The process of pooling the data into groups of similar location characteristics was iterative and exploratory. Although the accessibility and income measures were determined early on, many of the approaches explored to classify locations had many limitations that effected the ability to meet primary objectives: to minimize the grouping size to five or six establishments per grouping. By exploring various methods—including k-means cluster analysis, factor analysis, percentile and Jenks breaks approaches, and *Manual* classification—we found that limitations satisfying this constraint would not likely be replicable unless the constraints were incorporated into a quantitative clustering process.

To capture the greatest variation in accessibility from our clusters, we applied a balanced clustering analysis with accessibility and income measures that were described previously (Malinen and Fränti 2015, 2014). Data reduction techniques like clustering analysis or factor analysis are often used to distill built environment information into operational place types or indices in trip generation research (Clifton et al. 2012; Schneider, Shafizadeh, and Handy 2015), but no existing approach in the transportation impact analysis field has dealt with the added constraint of minimizing groupings to a balanced level. K-means clustering algorithms balance one objective—reducing the mean squared error (MSE) for the group of clusters—and balanced k-means clustering algorithms balance two objectives—reducing MSE and balancing the number of observations in each cluster. By using a balance-constrained approach, linear programming ensures that balanced clusters are a priority. In comparison, balance-driven approaches make balancing clusters a secondary priority (Malinen and Fränti 2014).

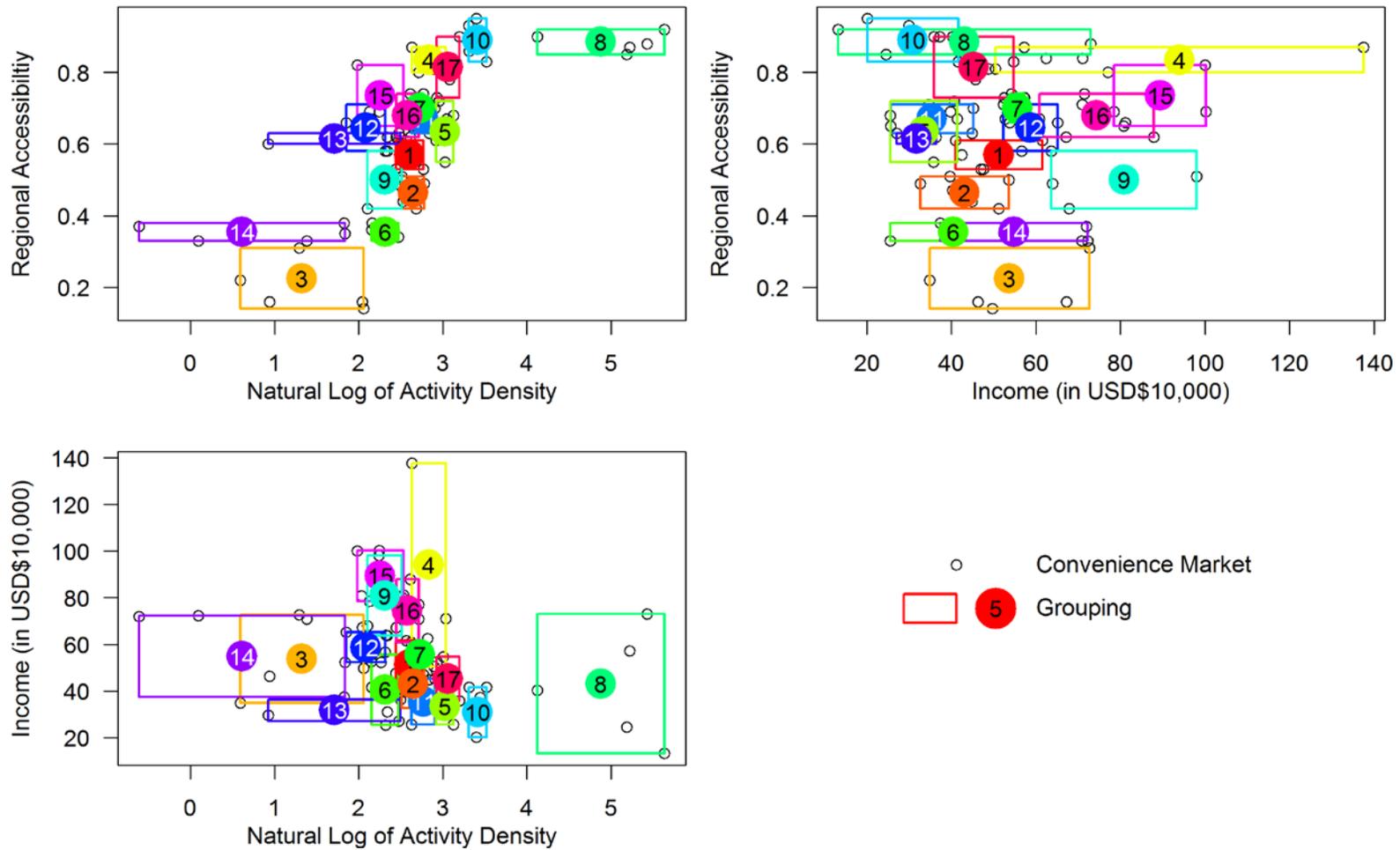
Using the three independent variables discussed in the previous data section, a balanced k-means cluster analysis was performed resulting in 17 clusters of four to six establishments each (See Figure 4-3).<sup>25</sup> Variables were first normalized by their mean to control for the varying range of variables—local accessibility, for example, ranged from

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<sup>25</sup> Observations collected in downtown Portland’s central business district (cluster 8) had substantially higher local accessibility (activity density) values and were later removed after identifying potential spurious results between activity density and transaction counts inflating the significance of the coefficients.

0 to about 280 people per acre while regional accessibility varied between 0 and 1.

Following, each of the three scaled variables (regional accessibility, local accessibility, and income) were weighted per their relative importance based on the literature review findings (3, 2, and 1, respectively).



**Figure 4-3 Balanced Clusters of Convenience Markets along Three Metrics: Regional Accessibility; Local Accessibility (transformation: natural log); and Median Household Income**

While an analysis of variation indicated that the clustering resulted in significantly different group means for all accessibility and income measures across the clusters, a post-hoc analysis indicated that 77% of the clusters, compared with others in the sample, had significantly different regional accessibility mean values; following, 43% and 29% of the clusters compared had different local accessibility and income mean values, respectively. This suggests, as intended, that the clusters best reflect variation in regional accessibility, followed by local accessibility and income. The main implication of using a group-level contextual variable average, instead of the individual site's variable, lowers the amount of variation in each contextual variable from 93 total locations to about 30 by masking the actual location of each establishment. As many have indicated with site-level transportation analyses, sample size is often a limitation of analysis, as it is in this study. Adding to this limitation, the requirement of masking location information in groups of five locations restricted the ability to observe variation in contextual information for these sites to 17 groups. Although the balanced clustering analysis allowed us to maximize variation across groupings, examining residuals on a more refined level remains impossible.

Although this manuscript would not have been possible without the donation of transaction data from the two partners who participated in this study, one major limitation of this analysis comes from the masking of individual data behind the balanced clusters created for convenience markets. Reducing the number of different contextual observations to one-fifth of the original sample size (clusters of approximately five stores), also limits the variation observed in the models, reducing the ability to examine

site-level errors. While small sample size is often a stated limitation in many transportation impact studies, here, the need to mask data manufactured it. Additional analysis simulating potential individual-level observations in instances where a certain level of masking is required may provide an understanding of the probability of finding significant relationships—and perhaps the distribution of potential relationships—given full access to the site locations. But this is an area for future analysis.

**Table 4-3 Descriptive Statistics of Dependent and Independent Variables, Including Regional Comparison**

	Convenience Market				Grocery Stores			
	Mean	St. Dev.	N	Range	Mean	St. Dev.	N	Range
<b>Observed Data</b>								
Locations	---	---	80	---	---	---	13	---
Weekly Transactions <i>[Counts]</i>	4,430	1,096	80	2,596 – 8,335	16,786	3,903	63	10,088 – 23,930
Daily Transactions <i>[Counts, all days]</i>	633	167	560	325 – 1,395	2,396	581	467	1,203 – 3,889
AM Peak Transactions <i>[Counts, all days]</i>	179	156	560	20 – 799	209	203	467	30 – 886
Midday Peak Transactions <i>[Counts, all days]</i>	235	214	560	26 – 957	226	201	467	26 – 873
PM Peak Transactions <i>[Counts, all days]</i>	293	283	560	30 – 1,086	208	185	467	27 - 854
Gross Floor Area <i>[1,000 SQFT]</i>	2.5	0.3	80	2.1 - 4.6	33.0	9.2	13	17.2 - 50.0
Precipitation <sup>1</sup> <i>[Total Inches]</i>								
Weekly <sup>4</sup>	26.7	---	80	---	5.1	3.2	63	0.0 – 9.4
Daily	< 0.1	0.1	561	0.0 – 0.3	< 0.1	0.1	482	0.0 – 0.41
<b>Contextual Information <sup>2</sup></b>								
<b>Observed Locations</b>								
Regional Accessibility <i>[Index {0,1}]</i>	0.60	0.18	80	0.20 – 0.89	0.63	0.16	13	0.37 – 0.87
Local Accessibility <i>[People per acre]</i>	13.3	6.5	80	3.6 – 30.0	16.1	7.6	13	2.0 – 32.6
Median Income <i>[2014 \$10,000 US Dollars]</i>	5.36	1.70	80	3.10 – 8.81	6.00	2.53	13	2.30 – 10.15
<b>Portland Region <sup>3</sup></b>								
	Mean		St. Dev.		N		Range	
Regional Accessibility <i>[Index {0,1}]</i>	0.50		0.21		1319		0 - 1	
Local Accessibility <i>[People per acre]</i>	12.7		18.0		1319		0.01 - 280.81	
Median Income <i>[2014 \$10,000 US Dollars]</i>	6.37		2.60		1319		1.10 – 20.99	
<b>NOTES:</b>								
<sup>1</sup> Sum of total inches observed on the day of data collection gathered from historic data supplied by WeatherUnderground.com for the location: Portland International Airport.								
<sup>2</sup> Collected from the Portland Metropolitan Area using the same variables as described in Table 4-2.								
<sup>3</sup> Calculated by block groups in the Portland, Oregon, area.								
<sup>4</sup> Convenience market observations were collected for the same week. Weekly summary of precipitation in total inches is constant for convenience markets.								
SQFT: Square footage								
St.Dev.: Standard deviation								

## Methods

To investigate the variation in transaction rates for the pooled data from these two land uses, three negative binomial regression analyses were completed estimating weekly, daily, and peak-hour transaction counts regressed upon our contextual characteristics (accessibilities and income), temporal variables (e.g., day of the week, time of day), a control variable for land use (e.g., grocery store or not), a covariate controlling for precipitation, and interactions of previously mentioned variables. Peak-hour counts represent the total transaction counts occurring during the peak period of the adjacent street (not of the generator). These times were segmented in an AM Peak (6:00AM to 9:00AM), a Midday Peak (11:00AM to 2:00PM), and a PM Peak (4:00PM to 7:00PM). Ideally, a control for store size should be established when predicting transaction rates; however, for both land uses, there was limited variation in the store size (see Table 4-3). Implications for variations in store size are explored in the discussion section.

Negative binomial regression was selected to account for the count-based nature of these data, but since the size of each establishment varied, an offset was used to control for the GFA in units of 1,000 SQFT, similar to the normalization of trip generation rates used in ITE's *Handbook* (Institute of Transportation Engineers 2014). This offset allows a control for the "exposure" of the site, in terms of establishment size and capacity to host customers, but the coefficient estimated from this offset is constrained to a value of zero. The corresponding interpretation of the model coefficients indicates a relationship between the independent variable and the dependent variable as expressed in a rate. In other words, the model is estimated as:

$$\ln(Y) = \beta_0 + \beta_k X_k + \beta_{offset} \ln(S),$$

where the transaction counts,  $Y$ , for establishments are regressed upon the  $k$ -number independent variables,  $X$ , and exposure,  $P$ . And where  $\beta_{offset}$  is constrained in estimation to a value of one such that the equation can be re-written as:

$$\ln(Y) = \beta_0 + \beta_k X_k + 1 * \ln(P),$$

or:

$$\ln(Y) - \ln(P) = \ln\left(\frac{Y}{P}\right) = \beta_0 + \beta_k X_k.$$

The estimated coefficients can then be interpreted as the relationship between the given independent variable ( $X_k$ ) and the rate of counts ( $Y$ ) per exposure ( $P$ )—which is GFA in this analysis.

For convenience markets (open 24-hours per day), we were provided with one week of transaction data—aggregated to a weekly rate and daily rates (by day of week)—from October 2015 for all 80 sites. For the grocery stores (open 14-hours per day), we were given three full weeks of data for one store (23 days total each) and five full weeks of data from 12 stores (37 full days' total), sampled from April 2013 and 2014. The result is 143 observations of weekly transaction counts, 1,027 daily transaction counts observations, and 3,081 observations of peak-hour counts for the 93 establishments.

Multiple analysis methods were considered to treat the repeated nature of the data, which violates the assumption of independent errors, inflating significance where there may be none. All methods (e.g., multilevel analyses, weighted repeated measures, random sampling) returned similar coefficients, direction of effects, and effects sizes, but

a negative binomial multilevel model form was chosen because it had the lowest Akaike Information Criterion (AIC) given the same independent variables and data. In this analysis, the level-1 variables were the transaction counts, aggregated first by week and then by day and peak hour. For the weekly data, the count data were nested within the establishment location (level-2). But for both daily and peak-hour models, the count data were first nested within a time-based level, week and day, respectively (level-2), and then within the establishment location (level-3). This was done to help control for repeated measures that were sampled so closely in time, and although this temporal nesting had little influence on the effect size of coefficients, it contributed significantly to reducing the overall AIC of both models and caused the significance of the location variables to change. The contextual variables, level-2 for the weekly model and level-3 for the daily and peak-hour models, included regional and local accessibility, income, and SQFT of GFA. Also included was a dummy indicating whether the establishment was a grocery store, as well as interactions between the grocery store dummy variable and the contextual variables.

Ideally, to detect contextual influences on level-1 outcomes (transactions), it is preferable to have sampled far more establishment-level observations, with fewer level-1 measurements than more level-1 measurements for a few establishment-level observations. This approach is ideal for datasets such as ITE's *Trip Generation Handbook* (2014) where volunteers often submit a few hours of data for each site, submitting more locations than observations from any one. In this case, we have 94 locations with between one to three observations weekly, one to six observations for each

day of the week, and three observations for each peak-hour period. Because data were selected from consecutive days within the three samples from 2013 to 2015, including these data in one model would require more sophisticated autocorrelation controls than the sample size allows. Instead, this is an area for future research and exploration.

To test for a mediated effect of the location variables (regional, location accessibility and income) on the distribution of transaction counts across the time of day and day of week, additional covariates representing the day of week and time of day are needed. Lastly, while controlling for the weather is a complex and nuanced process, an attempt was made to control for potential variations from sampling in the spring and fall of three separate years by incorporating a variable for precipitation (inches of rain) acquired on the day of observation (or aggregated for the weekly transaction counts).

## **Results**

Before the results of these analyses are interpreted, we remind the reader that all outcomes were regressed upon the independent variables while using an offset of the natural log of the GFA (in 1,000 SQFT). All coefficients are interpreted in terms of how each independent variable relates to transaction counts per 1,000 SQFT.

**Table 4-4 Negative Binomial Multilevel Model with Repeated Measures: Weekly, Daily, and Peak-Hour Transaction Counts (per 1,000 SQFT of GFA)**

<b>Dependent Variable, Counts:</b>	<b>Weekly</b>			<b>Daily</b>			<b>Peak Hour</b>		
Observations	143			1,027			3,081		
Log Likelihood	-1,225.38			-6,253.14			-19,215.01		
Akaike/ Bayesian Inf. Crit.	2,473 / 2,505			12,546 / 12,645			38,486 / 38,655		
	<b>β</b>	<b>S.E.</b>		<b>β</b>	<b>S.E.</b>		<b>β</b>	<b>S.E.</b>	
Intercept	7.80	0.15	***	5.79	0.14	***	4.91	0.27	***
Type of establishment (base: conv. markets)									
Grocery ±	-2.26	0.50	***	-2.17	0.50	***	-5.33	0.59	***
Locational Variables									
Regional Accessibility	-0.18	0.29		-0.18	0.28		-0.38	0.54	
Activity Density	0.01	0.01		0.01	0.01		0.00	0.02	
Income (\$10,000s)	-0.04	0.02	.	-0.04	0.02	.	-0.13	0.04	**
Location Variable * Grocery									
Regional Accessibility *									
Grocery	0.82	0.76		0.82	0.76		4.17	0.77	***
Activity Density * Grocery	0.01	0.02		0.00	0.02		-0.05	0.02	**
Income (\$10,000s) * Grocery	0.07	0.04	.	0.07	0.04	..	0.26	0.06	***
Day of the week (base: Friday) ±									
Monday				-0.09	0.01	***	0.13	0.05	*
Tuesday				-0.07	0.01	***	0.07	0.05	..
Wednesday				-0.01	0.01		0.17	0.05	**
Thursday				-0.05	0.01	***	0.12	0.05	*
Saturday				0.00	0.02		0.00	0.06	
Sunday				-0.08	0.01	***	0.10	0.05	.
Location Variables * Day of the Week									
Activity Density * Weekend				-0.01	0.00	***			
Activity Density*Weekend*Grocery				0.01	0.00	***			
Peak Hour (sum of 3-hour peak)									
AM (6-9AM) base							(base)		
Midday (11AM-2PM)							0.32	0.16	*
PM (4-7PM)							0.56	0.17	***
Location Variables * Peak Hour									
Regional Accessibility * Midday							-0.38	0.28	..
Regional Accessibility * PM							-0.62	0.28	*
Activity Density * Midday							0.00	0.01	
Activity Density * PM							0.01	0.01	
Income (\$10,000s) * Midday							-0.00	0.02	
Income (\$10,000s) * PM							0.03	0.02	..
Peak Hour * Grocery									
Midday * Grocery							-0.06	0.07	
PM * Grocery							-0.49	0.07	***
Precipitation (inches)									
Weekly Total	0.00	0.00	.						
Daily Total				-0.04	0.03	..	-0.17	0.16	

**NOTES:** "\*\*\*\*": p-value ≤ 0.001; "\*\*\*": p-value ≤ 0.01; "\*\*": p-value ≤ 0.05; ".": p-value ≤ 0.1; "..."": p-value ≤ 0.2. ± Dummy Variable; GFA: Gross Floor Area; SQFT: Square Footage

An offset was used to normalize transactions by the exposure, measured in establishment level GFA in 1,000 SQFT and transformed using the natural log.

### *Elasticities*

To examine the relationship between our variables of interest and transaction counts at each of the three temporal scales, we calculate the elasticities,  $\eta$ , as it relates to the transaction counts,  $Y$ , and each variable of interest,  $X$ . In other words,

$$\eta = \frac{dY}{dX} * \frac{X}{Y}.$$

Because a negative binomial model was applied, the elasticity may be expressed as:

$$\eta = \frac{dY}{dX} * \frac{X}{Y} = \beta_1 X,$$

Where  $\beta_1$  expresses the coefficient estimated for the variable of interest and interaction (dummy) variables were zero, or:

$$\eta = \frac{dY}{dX} * \frac{X}{Y} = (\beta_1 + \beta_2)X,$$

Where  $\beta_2$  expresses the coefficient estimated for the variable of interest interacted with a dummy variable with a value of one.

Table 4-5 through Table 4-7 indicate the elasticities calculated for each of three models: weekly, daily, and peak-hour transaction counts, respectively. A calculation was provided for each of the three variables of interest for each of the two land uses, and (for the peak-hour model) the three peak-hour time periods. The value for  $X$  is taken at the mean observed values, given the land use in question. Elasticities are interpreted as a percent change in transaction counts for a percent change in the variable of interest.

**Table 4-5 Weekly Counts Model: Computed Elasticities for Location Variables, by Establishment Type**

Locational Variables (X)	Establishment Type:	
	Convenience Market	Grocery Store
Regional Accessibility	-0.11	0.40
Activity Density	0.13	0.32
Income (\$10,000s)	-0.21	0.18

NOTES:

Coefficients multiplied by average observed values.

**Table 4-6 Daily Counts Model: Computed Elasticities for Location Variables, by Establishment Type**

Locational Variables (X)	Establishment Type:	
	Convenience Market	Grocery Store
Regional Accessibility	-0.11	0.40
Activity Density	0.13	0.16
Income (\$10,000s)	-0.21	0.18

NOTES:

Coefficients multiplied by average observed values.

All values represent weekday travel.

**Table 4-7 Peak-hour Counts Model: Computed Elasticities for Location Variables, by Establishment Type**

Locational Variables (X)	Establishment Type:					
	Convenience Market			Grocery Store		
	AM Peak	Midday	PM Peak	AM Peak	Midday	PM Peak
Regional Accessibility	-0.11	-0.34	-0.48	0.40	0.16	0.01
Activity Density	0.13	0.13	0.27	0.16	0.16	0.32
Income (\$10,000s)	-0.21	-0.21	-0.05	0.18	0.18	0.36

NOTES:

Coefficients multiplied by average observed values.

### *Interpretation*

The results from all three models suggest no significant direct relationship between transactions at weekly or daily temporal scales and regional accessibility (the Regional Centrality Index, which correlated highly with distance to the CBD). The peak-hour model, however, suggests relationships between transaction counts and regional accessibility were found to be significant and positive for grocery stores, but not significant for convenience markets. Additionally, the interaction between PM and midday peak hours were found to be negative, compared with that of the AM peak hour that are significant and marginally significant, respectively (p-values = 0.03, 0.17, respectively). This suggests that there is not enough evidence to suggest a relationship between regional accessibility and transaction counts at a weekly, or even a daily, temporal scale. The distribution of trips within a given day may vary by regional accessibility—observing a greater sensitivity to regional accessibility, on average, during the AM peak hour than midday or PM peak hour, all else equal. In terms of elasticities, these relationships, controlling for all else, suggest that transactions during the AM peak hour have a higher elasticity (0.4, Table 4-7) compared with the midday and PM peak hours (0.16 and 0.01, respectively, Table 4-7).

For local accessibility—defined as activity density, which was earlier found to have a high correlation with the real market value of commercially zoned land and competition to similar and potentially substitutable businesses—there was not enough evidence to suggest a significant relationship between weekly or daily transaction counts. However, it appears that a significant, albeit small, relationship exists between

transactions and the interacted effect of activity density and weekend days for both land uses ( $p$ -value  $< 0.001$ ). This suggests a slightly higher sensitivity of weekend to local accessibility for grocery stores ( $\beta = 0.01$ ), and a slightly lower sensitivity for convenience markets ( $\beta = -0.01$ ). For peak-hour travel, there was not enough information to detect a significant relationship between transaction counts and convenience markets. But for grocery stores, the results suggest significantly less sensitivity to activity density ( $\beta = -0.05, p - value = 0.01$ ). There was not enough evidence to suggest a significant relationship between transactions and local accessibility across peak hours.

An examination of relationships between transactions and median income reveals several significant effects that may be observed. Higher levels of median income relate to higher weekly transitions for grocery stores ( $\beta = 0.07, p - value = 0.10$ ), but to a lower number for convenience markets ( $\beta = -0.04, p - value = 0.08$ ). The models that estimated daily transition counts found similar relationships. While examining the peak hour, the direction of the relationship between transactions and income remain the same; however, the effect size and significance increases for both convenience markets ( $\beta = -0.13, p - value = 0.005$ ) and grocery stores ( $\beta = 0.26, p - value < 0.001$ ). The relationship strengthens somewhat during the PM peak hour, making it marginally significant compared against the AM peak hour ( $\beta = 0.03, p - value = 0.108$ ). In terms of elasticities, this shows an increase in the relationship between income and peak-hour transaction counts to 0.36 during the PM peak hour, from 0.18 during the AM and

midday peak hours for grocery stores, and an increase to -0.05 during the PM peak hour, from -0.21 during the AM and midday peak for convenience markets.

The relationship between weather and travel choices is a complex one; the authors cautions interpretation of significant, effect size and direction of coefficients estimated for weekly or daily precipitation. While this variable was found to make a marginally significant contribution for the explanation of additional variance in the model (p-value < 0.2), the values are obtained at an aggregate metropolitan level for each survey day, which may result in an inflated sense of significance.

## **Conclusions**

The hypothesis tested in this analysis was that variation in transaction rates, tested as a proxy to overall activity or person-trip rates at these retail food establishments, is related to regional and local accessibility as well as income. While there was not enough statistical evidence to suggest a significant relationship between varying urban contexts—in terms of regional and local accessibility and weekly and daily transaction rates—there was for median income of the surrounding area. While much of the literature on traffic impact analysis estimation has focused on urban form as the main contextual effects—e.g., (Ewing et al. 2011; Schneider, Shafizadeh, and Handy 2015; Clifton, Currans, and Muhs 2015)—few have recognized the importance of sociodemographic characteristics of the potential market of retail establishments as it relates to transportation impacts, in this case, person-trip rates. Furthermore, the results indicate other significant effects that modify the relationships between transactions and regional accessibility and median income, suggesting the contextual effects to be relative to the time in which counts are

being measured. As many transportation impact analyses are focused in the PM peak hour, these results suggest relationships derived during the AM peak hour may not hold for the midday and PM peak hour.

This analysis aims at understanding the relative variation in transaction rates within a region, particularly for transportation impact studies focused on overall estimation of activity. Many existing approaches that allow practitioners to adjust for urban form require a non-count adjustment (such as mode share) of base-case estimates, generally ITE's vehicle-trip rates. The assumption being that ITE's vehicle-trip rates reflect suburban area-types, and adjustments account for relative changes in behavior in more urban contexts. There exists limited if any information about the sociodemographic contexts of ITE's data (or other count data for that matter). Therefore, adjusting existing methods for sociodemographic variables, such as area-wide income, become problematic when there exists no baseline of trip rates for "average income" establishments, particularly for non-residential land uses. More research and data collection is necessary to understand the scale of this variation and the influences on trip generation estimates.

This manuscript focuses on two firms developed within one region. While this helps to control for the variation in each firm's target consumer market—specifically in reducing variation in cost, quality, and type of products, as well as marketing strategies—the rates derived in this analysis may not reflect average convenience market or grocery store location decisions. The monadic and tactical decisions made within these firms to create more efficient and productive establishments at all locations could possibly offset the relationships between consumer activities (transaction counts and person trips) and

the location characteristics (local and regional accessibility and access to targeted income markets), dampening benefits from accessibility and locating near target consumer markets. For future studies, ideal study location selection would include a random sample of locations picked across space, controlling for the multilevel hierarchy of establishments within firms (e.g., multilevel modeling). Similarly, while this analysis controlled for the multilevel nature of these days in time and space, no controls for spatial correlation were included in this analysis.

Although this manuscript would not have been possible without the donation of transaction data from two partners, one major limitation of this analysis comes from the masking of individual data behind the balanced clusters created for convenience markets. Reducing the number of different contextual observations to one-fifth of the original sample size (clusters of approximately five stores), also limits the variation observed in the models, reducing the ability to examine site-level errors. While small sample size is often a stated limitation of many transportation impact studies, here, the need to mask data created this limitation. Additional analysis simulating potential individual-level observations in instances where a certain level of masking is required may provide an understanding of the probability of finding a significant relationship—and perhaps the distribution of potential relationships—given full access to the site locations. But this is an area for future analysis.

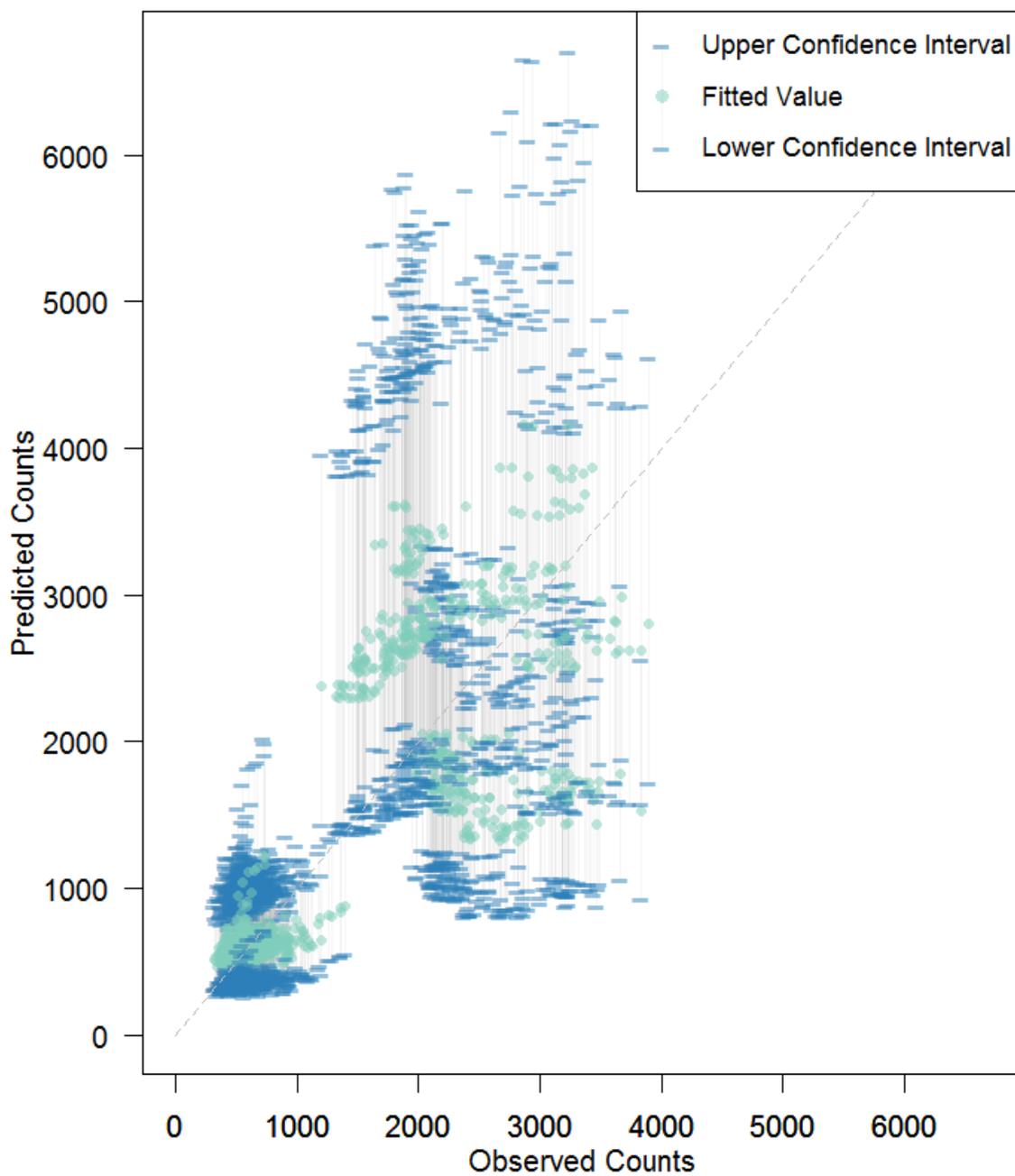
While these findings point to the need to understand and control for contextual variables beyond urban form in transportation impact analyses, the limitations in the variation and sample capturing accessibility and income warrant the use of these methods

in applications of transportation impact analyses only with caution. A better understanding is needed to identify the relationship between transaction counts and person-trip counts—a function that is likely related to group size and the duration of the customer's stay. With high on-site, transportation-impact-analyses data and the increased demand for person-trip counts, transaction counts may provide a valuable proxy, especially as they are often being collected for many different commercial land uses.

Moreover, the two datasets pooled in this analysis came from two different regional chains. While this allows the ability to control for potentially confounding factors—such as retail culture, price point or product selection (Brown 1992)—counts estimated from these models may not reflect average counts for other regions. Additional regional analyses are necessary to identify intraregional relationships between overall activity, in this case shopping at grocery and convenience markets, and accessibility to income markets or destinations—defined as either local or regional.

The method of analysis, negative binomial multilevel models, for estimating a more refined temporal level of analysis (such as hourly) appears promising. Multilevel analysis with a count-based model form, here a negative binomial regression, provides a way to interpret contextual level effects (accessibility, density, income) on trip rates. By nesting hourly counts within contextual variables describing establishment-level (or even area-wide level) analysis, one may be able to consider multiple temporal exposures, pooling peak-hour counts as well as 24-hour counts into the same models. The next steps of this analysis consider just that, an approach that utilizes controls for both contextual and temporal effects.

Although the methods presented in this paper (multilevel, multivariate, negative-binomial regression at multiple temporal scales) are more statistically rigorous compared with practical methods (univariate linear regression), it is important to emphasize the inherent uncertainty in any method of estimation—especially if used for prediction. To explore this, we examine the fitted versus the observed transaction counts (see Figure 4-4) for grocery stores using the “daily” temporal scale model (see: Table 4-4). Because a multilevel model was estimated, we examine a 95% confidence interval of predicting the fitted value through a bootstrapped approach—estimating the model for each observation 1,000 times, each with a randomly selected value drawn from the distribution of random variables estimated from the contextual level, and then calculating the confidence interval. Although the methods control for the count-based nature of the data, a wide range of prediction is observed, even for locations from which the given model was estimated. For transportation impact studies that so often call for expanding the vehicle network, rarely is the uncertainty of the prediction methods brought into discussion.



**Figure 4-4 Bootstrapped 95% Confidence Interval for Estimated Daily Transaction Counts at Grocery Stores, Compared with Observed Daily Counts**

## CHAPTER 5 COMPOUNDING OVERESTIMATION OF AUTOMOBILE TRAFFIC IN TRANSPORTATION IMPACT STUDIES: A CASE STUDY

### Introduction

Many agencies rely on trip generation estimates to evaluate the transportation impact of land development. Over the past decade, substantial attention has been paid to one set of national guidelines—the Institute of Transportation Engineers’ (ITE) *Trip Generation Handbook* (2014) and corresponding *Trip Generation Manual* (2012), referred to interchangeably within this manuscript—focusing in particular on critiquing the suburban, automobile-oriented nature of the data. Several projects have focused on the lack of sensitivity of these widely used data to urban context (Clifton, Currans, and Muhs 2015), smart growth areas as studied in phase I (Schneider, Shafizadeh, and Handy 2015) and II<sup>26</sup> of California projects, mixed-use areas (Bochner et al. 2011; Ewing et al. 2011), and transit-oriented development (Ewing et al. 2017). Others improve the representation of varying types of residential housing characteristics, such as reduced or paid parking environments (District Department of Transportation 2015), affordable housing<sup>27</sup>, or new housing products (e.g., micro- or zero-parking apartments)<sup>28</sup>. Many of

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<sup>26</sup> Ongoing project funded by Caltrans, led by Brian Bochner of Texas A&M Transportation Institute.

<sup>27</sup> Ongoing project funded by Caltrans, led by Kelly J. Clifton of Portland State University (PSU).

<sup>28</sup> Project funded by the National Institute for Transportation and Communities (NITC), led by Kelly J. Clifton of PSU.

these studies have been incorporated into the third edition of the ITE's *Handbook* and the upcoming updates (Bochner et al. 2016), and reviews and validation of these methods are available elsewhere (Currans 2017; Currans and Clifton 2015; Sandag 2010; Shafizadeh et al. 2012; Weinberger et al. 2015).

Despite these recent studies, there are still a number of limitations that persist in the existing practice. Many new approaches, for example, continue to rely on ITE's *Handbook* vehicle data as a baseline for adjustment (Currans 2017), despite a lack of sensitivity to known influences of travel behavior—such as the built environment and demographics— potentially/likely resulting in a biased estimate of automobile demand, inflating the costs and requirements on new development. Agencies also remain dependent on existing suburban *Handbook* data despite their urban contexts (Bochner et al. 2011; Clifton, Currans, and Muhs 2015). ITE's data continue to be applied in multiple aspects of the land development process, including, but not limited to: transportation or traffic impact analyses and studies (TIAs/TISs); scaling and scoping of development; and system development charges, impact or utility fees. Limitations of these data related to their temporal, spatial, and social contexts propagate into many aspects of the land development process.

The purpose of this study is to explore the issues in the data and methods provided in ITE's *Trip Generation Handbook*, comparing with theories and research of travel behavior, and to quantify the bias introduced into the development process. ITE explains that “an example of poor professional judgment is to rely on rules of thumb without understanding or considering their derivation or initial context” (Institute of

Transportation Engineers 2014, 3). The objective of this manuscript is to improve understanding of these widely-used data to encourage increased engagement with their context. From here, the users (engineers, planners, agencies, developers) can make more informed decisions about the application of ITE's data for varying contexts and applications.

## **Methods**

Since the ITE's *Handbook* starts that their data collection in the 1960's (2014, 7), there have been substantial improvements to the state of the knowledge in the travel behavior literature. There exist many innovative methods that attempt to control for some of this bias—most notably influences of the built environment (Chapter 2). However, there is no proof that these methods have been widely accepted in practice. And the implications of ignoring this research—in applying ITE's data without adjustment for these contexts—may result in the severe overestimation of vehicle demand corresponding with biases in estimates of impact fees or charges and/or overbuilding of automobile facilities.

The aim here is to align the context of ITE's data with existing research and studies—identifying any means (data, research, methods) to quantify any potential direction and degree of bias. These findings are separated into their respective temporal, spatial, and social contexts in the results section. Then, these findings are summarized with a demonstration of the cumulative impacts.

This manuscript focuses on a single data set: ITE's *Trip Generation Handbook* (2014) and *Manual* (2012). In the following section, we discuss the data itself—including

a description what the data are, how they are used, and how they were accessed for this analysis. Then, the methods for this analysis are described. The results section explores issues along temporal, spatial, and social contexts identified when comparing ITE's data to previous research. Where possible, quantifiable impacts are identified and referenced.

For many of the issues identified throughout the results section, there is not sufficient quantitative evidence to directly quantify impacts. These are areas for future research. Issues we can quantify are explored further, in the section "Summary and Case Study" on page 157. Impacts are then independently and cumulatively estimated for two land use cases (supermarkets and convenience markets) along three spatial scenarios (suburban, general urban, and urban district) and three demographic scenarios (high-, moderate-, and low-income levels). The cumulative results indicate inflated estimates of automobile demand in all scenarios. The implications of these results are discussed in the conclusion.

### **Data - ITE's *Trip Generation Handbook***

For many agencies, the ITE's *Handbook* provides the basis to evaluate the transportation impacts of land-use development. These data provide the trip generation counts of vehicles coming to and going from a site; for simplicity, we refer to these counts as "trip ends" and "trips" interchangeable in this manuscript. Up to the 9<sup>th</sup> Edition, the data in the *Manual* includes only vehicle counts, primarily collected in suburban locations where sites include only a single land use (no mixed use), have free and ample

parking, with little to no transit, bike or walking trips (Institute of Transportation Engineers 2012)<sup>29</sup>.

Trip rates are provided for a variety of land uses types in three forms: (1) in average trip generation rates, in counts per independent variable (usually square footage, number of dwelling units, employees); (2) graphical representation of them plotted against the independent variable, and; (3) in equations, where the counts are regressed upon one independent variable. Rates are provided by land use and time period (weekday, weekend, AM or PM peak hour of the adjacent facility, AM or PM peak hour of the generator). Guidance is provided within the *Handbook* for selecting one of the three rate forms (average rate, graphics, or equation) (2014).

Equations are only provided for land uses where the estimated explanation of variance,  $R^2$ , is greater than or equal to 0.5 and where there are four or more data points. About one-third of the rates have equations. In ITE's *Handbook*, trip rate equations are generally formulated as either linear or log-log regressions, as follows:

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<sup>29</sup> The 3<sup>rd</sup> edition *Handbook* (Institute of Transportation Engineers 2014) and the forthcoming 10<sup>th</sup> edition *Manual* (Bochner et al. 2016) include urban data—both multimodal person and vehicle trip generation counts. These new data are often called “urban” data, while the older suburban data are called “baseline” data. These urban data are currently available limited quantity and transparency. The current aim of ITE's Expert Panel on Urban Trip Generation is to provide guidance on how to use them. This manuscript focuses on the “baseline” data in the most recent edition of the data within the *Manual* (Institute of Transportation Engineers 2012).

$$T = \beta * IV + \beta_0 \quad \text{or} \quad \ln(T) = \beta * \ln(IV) + \beta_0,$$

where T and IV represent vehicle trips and the independent variable, respectively.

And  $\beta_0$  and  $\beta$  are the estimated constant and coefficient, respectively. ITE provides estimated univariate equations for each independent variable provided there are (a) four or more observations for the given land-use category, time period, and independent variable, and (b) the  $R^2$  value (unadjusted by sample size<sup>30</sup>) is greater than 0.5 (2014, 23). If these regression standards are not met, the average weighted trip rate is provided:

$$\overline{RATE}_{weighted} = \sum_{i=1}^N \frac{IV_i}{\sum_{i=1}^N IV} \left( \frac{T_i}{IV_i} \right) = \frac{\sum_{i=1}^N T_i}{\sum_{i=1}^N IV_i}.$$

### ***Convenience Sample***

It is also worth noting that the sites selected for inclusion in ITE's *Trip Generation Handbook* are not a random sample attempting to proportionately represent similar businesses or land uses across the United States. These data are a convenience sample, primarily offered as donations from data collections. Without adequate location information, the characteristics of the site and environs are unknown. However, the *Handbook* does specify that the majority of data provided are from "low-density, single-

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<sup>30</sup> Although the threshold  $R^2$ -value does not consider adjustments for smaller sample sizes, providing adjustments for sample size would reduce many of these equations, although only by a small amount. Only 5% of them will change more than 10% of the original  $R^2$ -value (16% would change more than 5%)—5% of the provided equations would result in an adjusted  $R^2$  of less than the 0.5 threshold the *Handbook* guidelines set for retaining the equation-form of the rate.

use, homogeneous, general urban or suburban<sup>31</sup> developments with little or no public transit service and little or no convenient pedestrian access” (Institute of Transportation Engineers 2014, 6)—although the proportion is unspecified. While one can assume this description does not likely represent *all* land-use categories—e.g., high-rise residential development are not likely to have all of those things—one may interpret this to mean that these sites represent only the most “suburban” of suburban contexts.

Furthermore, ITE’s data include a non-random convenience sample, data donated by industry and agency practitioners, and academics from the US and Canada. There is no public information on how many observations are provided by each donation source. It may be assumed that these data either come from (1) a research study, or (2) transportation impact studies. Data from the former may include larger sets of data across a wider range of contexts, but are likely collected within a smaller number of regions or cities. There are many potential reasons why a TIS analyst would collect new data: (a) there may not be any data for the land use being studied, (b) the available data may not represent the spatial, temporal, or social contexts of the study location, (c) the agency

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<sup>3131</sup> “General urban (GU)” and “general suburban (GS)” area-types are defined by ITE’s 3<sup>rd</sup> edition *Handbook* (Institute of Transportation Engineers 2014). GU was only recently added in the 3<sup>rd</sup> edition, and does not reflect data included in the 9<sup>th</sup> edition *Manual* (Institute of Transportation Engineers 2012), which are still considered primarily suburban. GU is generally defined as areas with slightly higher densities (low to medium) with a mix of residential and commercial uses and occasional industrial, institutional, or educational uses.

may require new local data be collected, (d) the proposed development may be on a problematic corridor that triggers a more thorough review, or (e) the developer or practitioner may feel ITE's rates are not representative of the proposed development. For all reasons but the first, the incentive to collect data may relate to observed changes in vehicle trip generation rates due to spatial, temporal, or social contexts. While the authors are not able to investigate motivations of donated data, we do explore the implications of temporal, spatial, and social contexts in the following results section.

### ***Compiling the Data***

To explore the variation in these rates across and within land uses, the authors were provided free access to ITE's data through the third party online website, OTISS. This website provides two variables not provided in the paper-edition of the *Handbook*: region (e.g., Pacific, Central, Mountain, or Eastern) and year of data collection (dating from 1907 to 2015).

Data were assembled through the online interface, querying across the age of the data and region. A small portion of trip rates lack either year or region of data. For the purpose of this analysis, these counts have been ignored. Some counts are shown with multiple independent variables (e.g., square footage, dwelling units, and employees). By examining data provided through ITE and OTISS, one cannot distinguish which data points were collected from the same location.

## Results

### *Temporal Contexts*

#### *Year Data Were Collected*

The years that each of ITE's *Handbook* data points were collected is a topic rarely discussed at length. The year associated with ITE's data can be obtained, for a fee, by using a third-party online system: OTISS. Using OTISS, data can be filtered by age and region (e.g., Pacific, Central, Eastern, and Mountain). This allows for more regional and temporal definition in analysis. In a descriptive analysis of ITE's 9<sup>th</sup> edition *Handbook* (2012), only 4% of data points provided were collected<sup>32</sup> between 2007 and 2017—half as much as collected prior to 1970 (8%)—and 23% collected between 1997 and 2017<sup>33</sup>. Figure 5-1 includes the distribution of data from 1955 to the present<sup>34</sup>.

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<sup>32</sup> We assume the date associated with each data point describes when the data are collected, making it a conservative quantitative exploration of age. However, it is possible this date describes the year in which the data were reported or submitted. Some reports may have included multiple data collections ranging from several years prior to the submittal.

<sup>33</sup> Recently, ITE conducted another successful periodic “call for data” with the hope of updating both the baseline and urban trip generation site counts, emphasizing the need for person trip generation data. They hope to incorporate these new data in the 10<sup>th</sup> edition of the *Manual*.

<sup>34</sup> Not included on this graphic: 1.1% of the data were collected prior to 1955, and 0.1% of data not associated with a date of data collection.

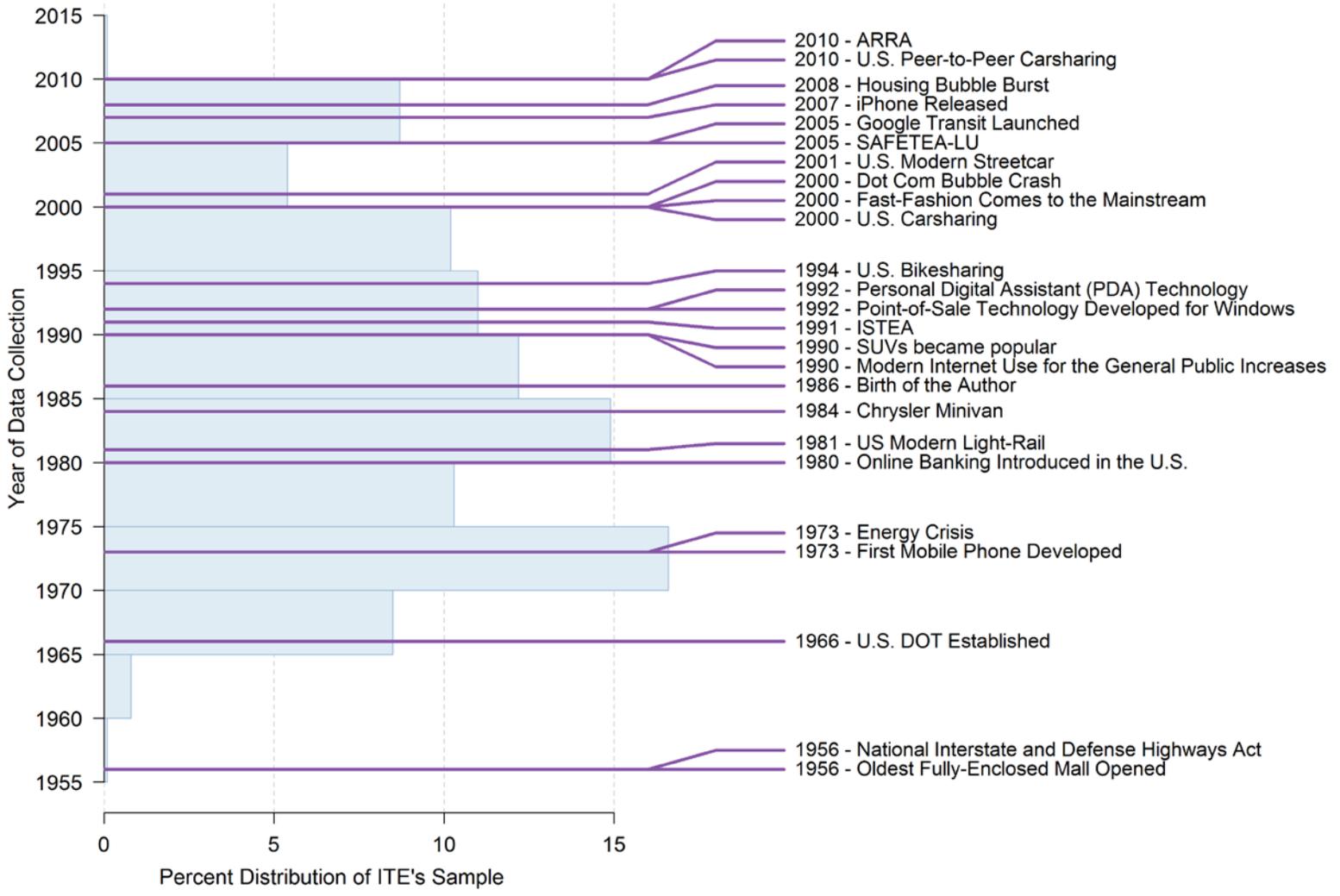


Figure 5-1 Temporal Distribution of ITE's Data Sample (left) and Timeline of Major Events (right, overlaid) (1955 to 2017)

Additionally, a rough timeline of major U.S. events that likely shape US travel patterns is shown in Figure 5-1. For example, four major pieces of legislation occurred<sup>35</sup>, each shaping the way that transportation networks are funded and implemented (e.g., interstates, transit networks, multimodal projects). Three major economic crises were noted (1973, 2000, and 2008), each tied to either constrained household budgets or rising prices for goods and/or travel. Within this period, carsharing and bikesharing entered the U.S., a resurgence of modern light-rail and streetcar systems were built and internet and smartphones were introduced. This punctuates the changes and transformations that have occurred during the time span for which ITE data represent. This is not to say that all of these events and innovations have led to observable changes in transportation and land use, but rather to note that a lot has changed. Applying these older data without considering how these events influence travel behavior is misguided.

Although sites with recent data are added to the ITE collection, there is no policy to sunset data or remove data from active use, but ITE does conduct “[s]tatistical tests including combinations of variations from averages, standard deviation expansion, clustering of recent data,  $R^2$ , T-tests, and F-ratios) [to] determine if differences are significant between older data and newer data” (Institute of Transportation Engineers 2014, 7). Results of these tests are not publicly documented. The only acknowledgement

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<sup>35</sup> The Federal-Aid Highway Act of 1956; the Intermodal Surface Transportation Efficiency Act of 1991; the 2005 Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users; and the American Recovery and Reinvestment Act of 2009.

of changing rates over time—based on a published note (to the best of the author's knowledge)—are for banking establishments collected prior to 2000. The note declares that walk-in and drive-in were determined to be significantly different (the method used was not identified). These data were removed from the publication (ITE User's guide, 8th edition, page 4). In 1985, Keller and Mehra found no statistical evidence when testing for differences in trip rates before and after the 1973 energy crisis (Keller and Mehra 1985a). There were no recommendations to remove data because of this analysis. The authors used t-tests to compare the differences between non-normal distributions, but the implications of this were not discussed. Instead, ITE's *Handbook* provides rates that are an aggregation of all data, an average with equal weighting of older and new data.

An analysis of eight of ITE's retail and service categories from the 9<sup>th</sup> Edition *Manual* (2012) found that the age of the data were significantly and positively related to the vehicle-trip rates for every category, with elasticities varying between 0.2% and 2.4% (see Table 3-7 and Table 3-8 in Chapter 3). This does not necessarily mean that rates decrease as time goes on. Instead, these results indicate that the vehicle-trip rates derived from older data inflate the amount of vehicle demand for today's contexts (Chapter 3).

Without more information about each data point, the causes of these significant changes in rates over multiple decades are difficult to untangle. The relationships between the age of ITE's data and patterns of data collection are ill understood. For example, this difference may be related to how site selection changed over time. It is also possible that overall variation in the costs of travel (e.g., fuel, vehicle ownership) have changed. Or that accessibility toward alternative modes have improved (e.g., as transit

networks expand to suburban areas). The number of sites and the year of data collection may also be associated with the growth (or decline) in development of specific industries. For example, recent requests for data on the ITE forum include marijuana dispensaries, a new and emerging land use. Similarly, data are often collected and donated in waves as part of larger studies, potentially correlating the year of data collection with trends in funding for larger studies.

Continuing to use these older data are not the standard practice in other parts of the world. In the United Kingdom, for example, data older than 10 years of age is decommissioned. They rely on an annual data collection that feeds back into general land-use categories and contexts (Trip Rate Information Computer System (TRICS) 2017). In other aspects of transportation planning, data are discarded or replaced with updated information, and for good reason. Other studies have noted changes in behavior over time as the relationship between trip-makers and land use changes with changes in technology, options, culture, and costs (Chandrasekharan and Goulias 1999; Nelson et al. 2015), and relying on old data biases estimates and forecasts (Flyvbjerg, Holm, and Buhl 2005). Specifically, behavior changes as transportation (or destination and activity) options become more/less accessible or costly. And there have been substantial changes in the world of transportation during the timeline within which most *Handbook* data were collected.

### *Defining Peak Hour*

Other temporal aspects of the data collection and processing protocols also lead to an inflated sense of vehicle demand, in part derived from the need to make conservative

assumptions in how we estimate and treat demand. The definition of “peak hour” is one of them.

For agencies that specify the guidelines against which development is evaluated, the peak hour is the most common time period (Clifton, Currans, and Muhs 2012; Bochner et al. 2011; Keller and Mehra 1985b), aligning the evaluation of development along with the worst time periods for vehicular traffic congestion on adjacent streets: the 7:00AM to 10:00AM peak and the 4:00PM to 7:00PM peak. To evaluate impacts, trip generation rates are identified in the *Handbook*. These rates are often referred to as “average peak hour” values, but a more apt designation should be “average maximum peak hour”. The difference in these small details is expressed and quantified in the following subsections.

Current methods require a two to three hour series of 15-minute counts to be collected during the morning and evening peaks<sup>36</sup>. The analyst then calculates a *moving hourly sum*<sup>37</sup> for each complete and consecutive hour of data collection (four 15-minute count periods). An example is provided in Figure 5-2 below. Here, person-trip counts were collected in 15-minute increments between 7:00AM and 10:00AM at a mixed use

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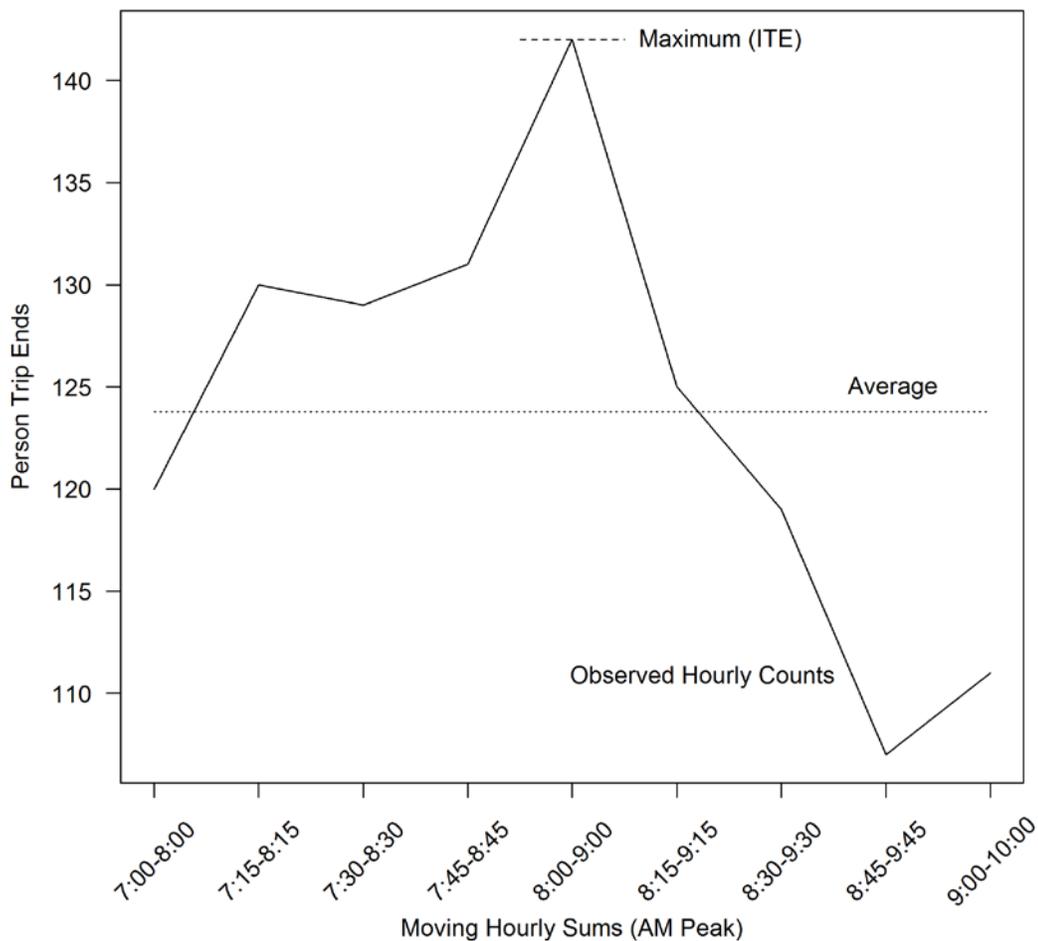
<sup>36</sup> The data collection form can be found online at <http://library.ite.org/pub/e278c427-2354-d714-5104-02d600087399> (accessed May 29th, 2017).

<sup>37</sup> Similar to a “moving, running, or rolling average”, a moving sum computes the hourly counts for each consecutive hour of data collection (four 15-minute counts).

residential development in Washington, DC by the District Department of Transportation, or DDOT (2015). Nine moving hourly sums were computed across the three hours of data collection, as depicted by the solid line. ITE, by definition, retains the highest complete and consecutive hourly count<sup>38</sup>—the *maximum moving hourly sum*—here depicted by the dashed line at 8:00AM to 9:00AM at just over 140 person trip ends. The average hourly count for this site—the *average moving hourly sum*—is depicted by the dotted line at just under 125 person trip ends.

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<sup>38</sup> The author could not find a written explanation for this subtle decision in the data processing protocols. The guideline to retain the “highest” consecutive hourly count comes not in the *Handbook* itself, but in a footnote on the recommended data collection and submission forms.



**Figure 5-2 An Example of Two Definitions of Peak Hour: Maximum (dashed line) versus Average (dotted line) (Data Source: DDOT (2015), Building ID #1, AM Peak)**

For this example, the percent difference between the *maximum* and *average* can be computed by taking the difference between the two and dividing by the *average*. While the *maximum* will always be greater than or equal to the *average* sum, in this example, the *maximum moving hourly sum* is 15% greater than the *average moving hourly sum*. To explore the variation in the difference between these two definitions, two data sets are explored.

Considering that all peak-hour data collected and processed within ITE's guidelines include the *maximum* sums, it can be deduced that the peak-hour average rates represent the highest volume of consecutive hourly traffic and not average conditions. To estimate how much these data collectively vary from a true peak-hour average, we explore the differences for two data sets: 62 residential and mixed-use residential buildings from Washington, DC (District Department of Transportation 2015), and 78 retail and service establishments from Portland, Oregon (Clifton, Currans, and Muhs 2015). To compute these differences all data—collected in 15-minute increments during the AM and/or PM peak periods—were converted into moving hourly sum counts, computing both the maximum count and the average count. The Portland, Oregon data were only collected between 5:00PM and 7:00PM in the PM peak, and therefore only five moving hourly sums were computed; the DDOT data, as described earlier, were collected during two three-hour peaks: 7:00AM to 10:00AM and 4:00PM to 7:00PM. The values computed represent the difference between the *maximum moving hourly sum* and the *average moving hourly sum* as a proportion of the total *average moving hourly sum*<sup>39</sup>.

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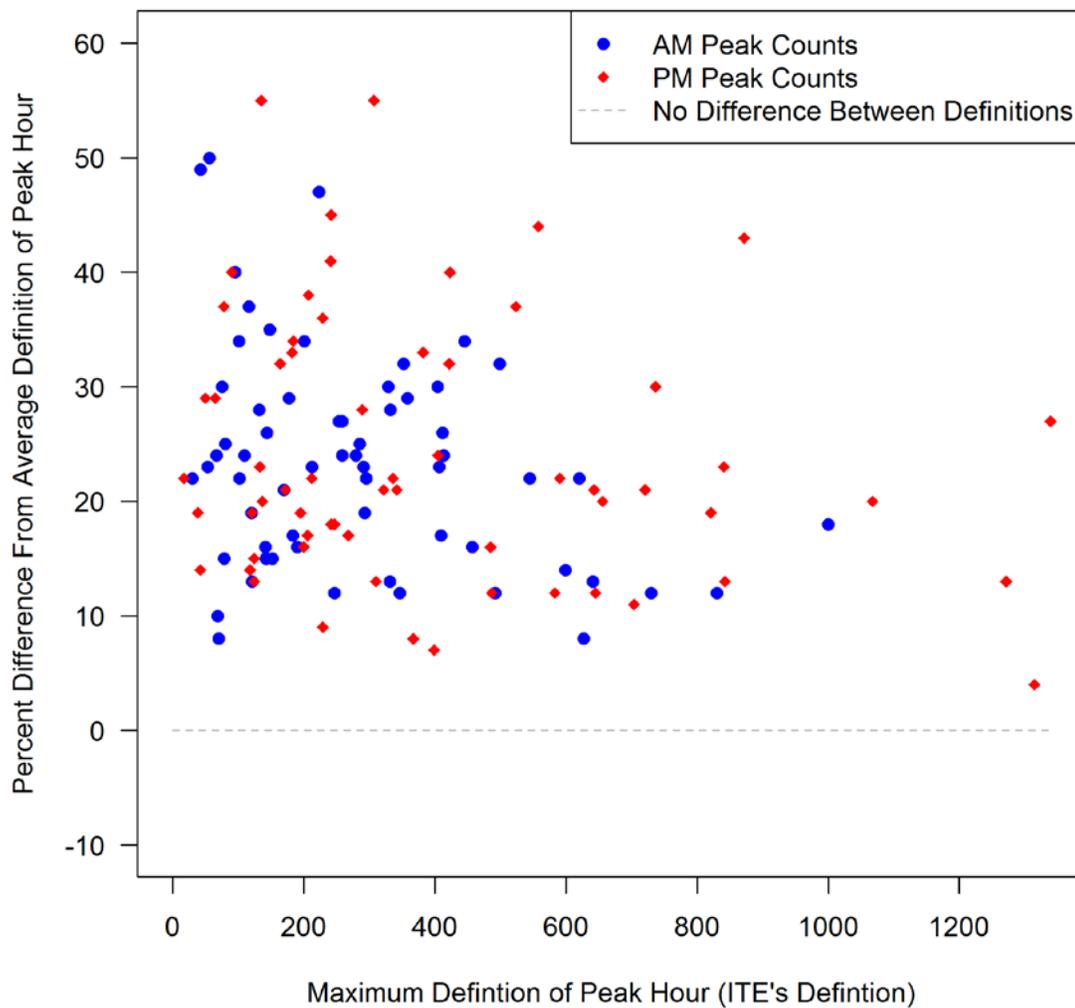
<sup>39</sup> Equation for reference: *Percent Difference* = 100 \*

$$\frac{\text{Maximum Moving Hourly Sum} - \text{Average Moving Hourly Sum}}{\text{Average Moving Hourly Sum}}$$

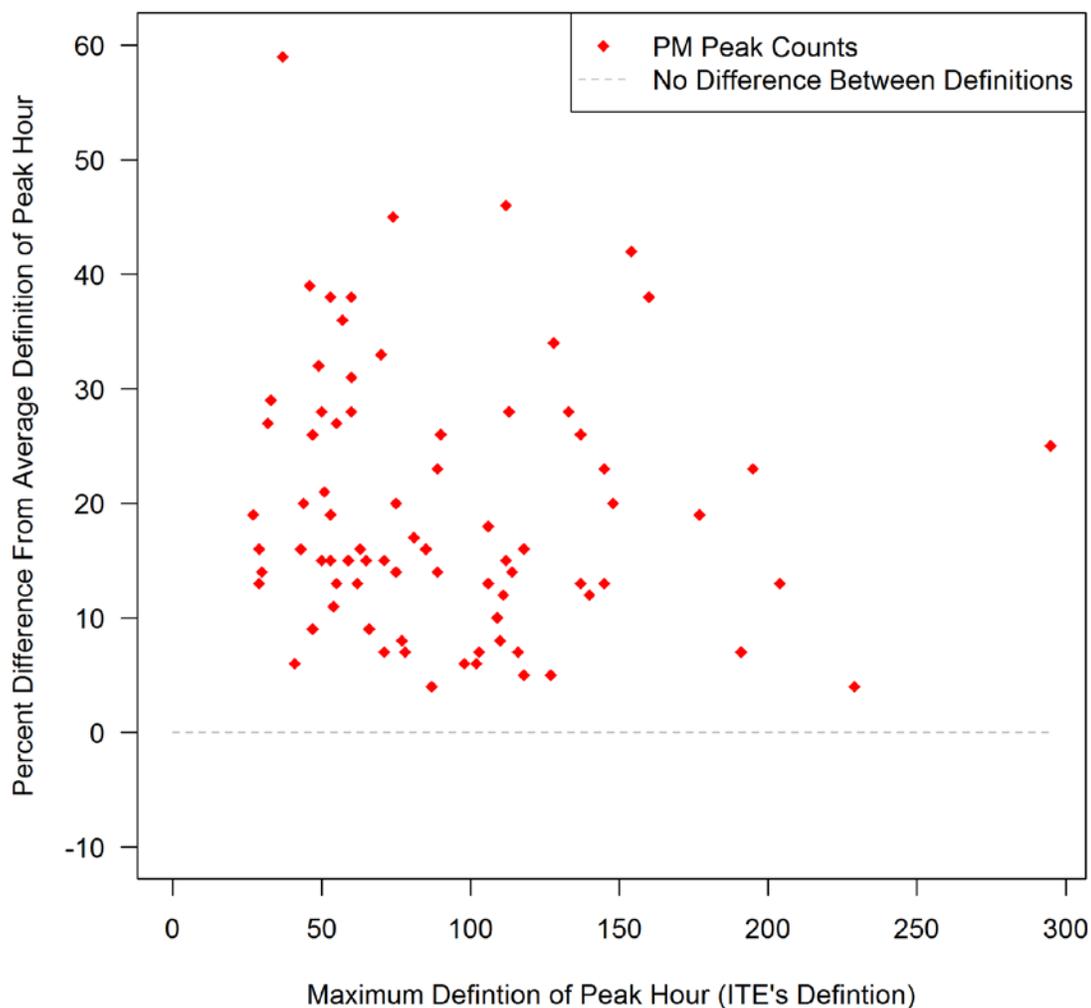
This percent difference represents how much higher the *maximum* sum is from the *average* sum in terms of total observed person trips<sup>40</sup>.

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<sup>40</sup> Although trips observed are often expressed as a ratio of counts to the exposure or size of development (e.g., dwelling units or square footage), these independent variables vary for the observed data sets. Additionally, the same variable would be used to compute both the *maximum* and *average* summations, canceling out the benefit of examining these data using rates in lieu of counts.



**Figure 5-3 Percent Difference between Definitions of Peak Hour for Residential Mixed Use: Maximum (ITE's Definition) versus Average Moving Hourly Counts (Data source: DDOT (2015), 62 Buildings, 3-Hour Peak Counts)**



**Figure 5-4 Percent Difference between Definitions of Peak Hour for Retail and Service Uses: Maximum (ITE's Definition) versus Average Moving Hourly Counts (Data source: Clifton (2015), 78 Establishments, 2-hour Peak Counts)**

Considering first the residential data (see Figure 5-4, top), the *maximum* definition contributed to an inflation of reported person-trip rates between 4% and 55%, or 23-24% on average for AM and PM peak periods. Similar results were found when examining the retail and service data (see Figure 5-4, bottom). The *maximum* count was between 4% and 59% higher—or on average 19% higher—than the *average* rate.

*Person Trips to Vehicle Trips, and Other Multimodal Information*

In the previous analysis, we use person-trip rates collected from two different studies to demonstrate the potential differences between these two peak-hour definitions. It is useful to note that ITE does not publish the 15-minute counts, but rather the summarized *Maximum* observed values. While ITE is moving toward including more multimodal data and methods—particularly the provision of person-trip counts (such as those discussed in the previous subsections), multimodal mode shares, and vehicle occupancy rates—this aspect of rate calculations remains the same (Institute of Transportation Engineers 2014).

It is generally understood that the primary benefit of ITE's *Handbook* is to aid in the evaluation of transportation impacts on new development—particularly when comparing the added traffic (estimated using ITE's rates and the volumes of existing traffic on adjacent facilities) (Keller and Mehra 1985b). Initially, the impetus for these data are to provide an quick reference method to estimate demand such that the adjacent facilities can be evaluated against corresponding vehicle performance metrics (e.g., level-of-service). However, when only a single performance metric is used for evaluation, the typical engineering response is to provide a conservative comparison, ensuring that failure is not likely to happen. Collecting the highest count during the peak hour, in lieu of an average count, is similar to building in a factor of safety. This ensures that when nearby facilities are evaluated, they will be less likely to fail in the worst case scenario: maximum observed peak-hour counts. The resulting data set includes the compiled averages of maximum peak-hour counts derived to be conservative, preventing the

potential underestimation of vehicle demand. The implications of this practice are explored in the Discussion and Conclusions sections later in this chapter.

### ***Spatial Contexts – Built Environment and Accessibility***

The travel behavior literature has established that observed behavior varies across different regional and local accessibilities (Handy 1992; Levine et al. 2012) and the conditions of built environment (Ewing and Cervero 2010; Stevens 2017). In fact, most of the recent studies focusing on improving the trip generation methods aim to account for the built environment and accessibility (Currans 2017); however, most of these methods continue to rely some adjustment of ITE's baseline suburban sites, making the assumption that all of ITE's data represent development within some average suburban context. Few have explored the context from which ITE's *Handbook* data are collected, and for good reason: ITE does not currently provide information on the location of each data point<sup>41</sup>.

ITE suggests submitted data be categorized by generic place types (e.g, Activity Center, Central Business District, General Suburban; see full descriptions in (Institute of

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<sup>41</sup> ITE is exploring improving the transparency of locations in newly collection data, including measures of the built environment and potentially some generic geolocation identification (e.g., census block group) in the upcoming update of *Handbook* (Bochner et al. 2016). They are also exploring the post-processing of older data to acquire more detailing information about each site with the hope that providing this information will spur more conscious considerations about the currently ubiquitous urban use of these suburban data.

Transportation Engineers 2014, 131)). Data are then sorted, mostly suburban sites being included in the *Handbook* data (Institute of Transportation Engineers 2014, 6). But perhaps not all “suburban” locations are created equal. In a 2015 study of retail and service establishments across the Portland metropolitan area, including suburban locations similar to those defined by ITE’s sites, the researchers found that sites generated an average of 20% mode share for walking, biking, and transit trips (Clifton, Currans, and Muhs 2012). Along those lines, some land uses are inherently more urban than the “suburban” assumption gives them credit. Spatial context is sometimes captured in the land-use category definitions (e.g., high-rise residential buildings with 10 or more stories).

Fortunately, there are several methods in development to control for spatial context, including: population and/or employment density, distance to central business districts or accessibility, and access to transit, to name a few (Schneider, Shafizadeh, and Handy 2015; Clifton, Currans, and Muhs 2015, 2015; Ewing et al. 2011).

### ***Social Contexts***

#### *Demographics*

Another aspect commonly associated with changes in observed travel is the trip-maker’s socio-demographic and economic characteristics. The travel behavior literature has long established a correlation between socio-economics and –demographic and travel behavior, with characteristics including, but not limited to: age, gender, household income, vehicle ownership, presence (and age) of children, and household size. In travel-

demand models, trip generation is modeled as a function of several social and spatial characteristics, the most popular including: income, car ownership, household structure, and family size (Willumsen and Ortúzar 2001, 126). These characteristics are a requirement for household activity survey collection (Willumsen and Ortúzar 2001, 77) as income or vehicle ownership of residents are often included in home-based travel behavior studies, e.g., (Guo, Bhat, and Copperman 2007; Ewing, Deanna, and Li 1996; Pas 1985). Developers often consider income—coupled with population distributions—during the location decision process (Hernández and Bennison 2000; Clarkson, Clarke-Hill, and Robinson, 1996).

These characteristics are rarely incorporated into evaluating development-level transportation impacts (Currans 2017), despite some direct evidence that supports its use. For example, a study by Reid (1982) compared home-based vehicle-trip rates from the 1979 National Personal Transportation Survey from the Southern California Association of Governments (SCAG) with ITE's residential rates. After controlling for income, household size, visitor and customer service trips—as well as access to transit—the author found that ITE over-predicted average SCAG households by 30%. For low-income housing, ITE's rates may inflate the vehicular demand further. In 2005, a national study of low-income adults found that a quarter of participants did not participate in out-of-home trips (Giuliano 2005). In California, two current studies are investigating the reductions in vehicle-trip rates for low-income housing citing the over-estimation of vehicular demand as a major barrier for developing affordable housing<sup>7</sup>.

The direction and size of the relationship between trip generation and demographics may vary for different land uses. In Chapter 4, the relationship between transaction counts—a proxy for person-trip counts—and income is evaluated for two retail land uses. For convenience markets, the results indicate that for every 1% increase in area-wide income (per \$10,000) we observe a 0.05% decrease in PM peak-hour transaction counts. For a similar increase in income, we observed a 0.36% increase in PM peak-hour transaction counts for grocery stores (see Table 4-7).

Despite this evidence, only three existing methods of trip generation estimation have tested for or include some demographics (see Table 2-3 in Chapter 2). First, Schneider (2015) found a significant and negative relationship between access to a university—a student population—and observed vehicle trips. This suggests that proximity to a university would result in lower observed vehicle trips, compared to ITE trip rates. Second, Ewing et al. (2011) found a significant and negative relationship between the household size of the trip-maker and home-based work trips, home-based other trips, and non-home-based trips. These results were echoed in a second paper by the same authors when they expanded the six-region study area to 13 (Tian et al. 2015). ITE's data occasionally controls for demographics through the land use definition, segmenting out "luxury" apartments or "discount" goods (Institute of Transportation Engineers 2012).

#### *Land Use Categorization*

It is also not clear that the extensive segmentation of land-use categories improves the accuracy of analysis. ITE's rates are segmented into over 170 different land-use

categories—more than a third of which represent retail and service uses. The variation explained by these classifications does not necessarily outweigh the costs of collecting enough of a sample for each category. Furthermore, these uses do not necessarily provide parity with the generalities of (1) zoned designations of land use (e.g., commercial, residential, industrial, mixed use), (2) transportation demand forecasting models (e.g., home-based work trips, home-based other trips, work-based other trips), or (3) activity purposes in household travel surveys (e.g., eating outside of the home, retail shopping for heavy goods, visiting friends)—all three of which supplement and support regional comprehensive plans for land use and transportation.

In Table 3-3, the statistical contribution of ITE's taxonomy is examined for retail and service land uses. The authors find little benefit in the variation explained by the 63 categories—compared with an aggregated classification of two indicators of land use (convenience land or heavy goods retail). And less so when considering the costs associated with the extensive data collection necessarily to populate a minimum sample (four observations) for each retail and service category (approximately USD\$2.1-2.7 over 10 years, which includes the sunset of data more than 10 years old).

### **Summary and Case Study**

In the previous results section, we examined several issues identified with the temporal, spatial, and social contexts of ITE's *Trip Generation Handbook* as they are applied directly by many agencies (Clifton, Currans, and Muhs 2015; Bochner et al. 2011) and indirectly in many innovative methods (Ewing et al. 2011; Clifton, Currans, and Muhs 2015; Schneider, Shafizadeh, and Handy 2015). For each of these methods, we

identified the results of each issue, as it relates to vehicle trip generation rates (see Table 5-1). Five major issues have been examined—four of which are addressed in this dissertation and the fifth was supported by the author’s thesis. For example, to control for the built environment, a mode share and vehicle occupancy adjustment model is applied (Currans and Clifton 2015, 100, 102). Adjustment A and C estimate adjusted vehicle-trip rates. Adjustment D estimates transaction counts—a proxy for activity levels—for different income levels.

Each of these studies explores the independent relationship of each issue to changing trip rates, but it is likely that these issues have some cumulative effect as well. In this section, the cumulative impacts of issues in urban trip generation estimation data and methods are quantified.

**Table 5-1 Result in Misapplication of Temporal, Spatial, and Social Contexts in ITE's Trip Generation Handbook**

<b>Contexts</b>	<b>Results</b>	<b>Adjustment</b>	<b>Method to Estimate Result</b>
<i>Temporal</i>			
Year data are collected	Increases vehicle demand	A	Chapter 3
Definition of peak hour	Increases vehicle demand	B	Chapter 5 - Figure 5-4 Summary
<i>Spatial</i>			
Built Environment	Increases vehicle demand	C	(Currans and Clifton 2015, 100, 102)
<i>Social</i>			
Demographics	Varies by land use and demographic	D	Chapter 4 – Table 4-4 Peak-hour Model
Land Use Categorization	Varies by land use	A	Chapter 3 - Table 3-7 Model M2 (b)

To demonstrate how these biases compound throughout vehicular trip generation estimation, we explore case studies of two retail land uses: convenience markets (open 24 hours, ITE land use code 851) and supermarkets (ITE land use code 851). Since context matters, three area type scenarios (suburban, general urban, and urban district) and three income scenarios (area-wide median annual household income at a high-, middle-, and low-level) are created. For each of these cases, scenario definitions are described (see Table 5-2). These variables are necessary to quantify each adjustment. Adjustment A from Table 5-1 is a constant value for all scenarios. Adjustment B is a simple equation that does not require additional information.

Table 5-2 Scenario Characteristics Considered for Case Study

	Units	Required for Adjustments	Scenario Definition		
			Suburban	General Urban	Urban District
<b>Built Environment</b>					
Regional Accessibility <sup>1</sup>	Unitless	Chapter 4	0.2	0.4	0.7
Distance to Central Business District <sup>2</sup>	Miles	(Currans and Clifton 2015)	8	6	3
Activity Density <sup>3</sup>	People per acre	Chapter 4	10	35	60
Population Density <sup>4</sup>	Residents per acre	(Currans and Clifton 2015)	8	25	40
<b>Demographics</b>					
			<b>High</b>	<b>Middle</b>	<b>Low</b>
Income <sup>5</sup>	Median Annual Household Income	Chapter 4	\$80,000	\$50,000	\$30,000

**Note:**

<sup>1</sup> Defined as Jobs accessible within a 45-minute drive, weighted by a travel time decay function and normalized by the regional total and maximum accessibility value at a block-group level (Regional Centrality Index), unitless; Smart Location Database, Variable D5cri.

<sup>2</sup> Defined as Euclidian Distance of Destination to the Regional Central Business District (CBD) in Miles.

<sup>3</sup> Defined as Sum of gross population and employment on unprotected land per acre at a block-group level; 2010 Smart Location Database, people per acre; Variable D1b + D1c.

<sup>4</sup> Defined as gross population on unprotected land per acre at a block-group level; 2010 Smart Location Database, residents per acre; Variable D1b.

<sup>5</sup> Defined as Median household income at a block-group level; 2014 American Community Survey (5-year), Variables B19013.

<sup>6</sup> The relationship between age and trip rate was not explored in Chapter 3 for supermarket land uses. Here we apply the findings from “shopping center” (land use code 820). Shopping center is often applied to supermarket development where additional retail development is included in the same site.

<sup>7</sup> The relationship between age and trip rate was not explored in Chapter 3 for the example “Convenience Market (24-hour)”. Here, the relationship identified for convenience market with gas station (land use code 853) is included.

The estimated percent error is defined by the following equation, and provided in

Table 5-3 for each land use and scenario.

$$Error = 100 * \frac{(ITE\ Estimate - Adjusted\ Estimate)}{Adjusted\ Estimate}$$

Suburban area-types reflect most of ITE's data. However, not all suburban area-types are alike. The quantitative descriptions of "suburban" area type are more "urban" than ITE's—thus even suburban areas, as defined in Table 5-2 are estimated to have less automobile demand than ITE. Additionally, ITE does not (yet) collect or provided demographics for their data. Here, we assume ITE's data represent an approximately median value of annual household income (\$50,000). Error is estimated for low- and high-income scenarios relative to this middle value. To adjust the original trip rate for each scenario, the percent error is then applied to the ITE's *Trip Generation Handbook* vehicle-trip rate, as described below:

$$\text{Adjusted Trip Rate} = (\text{ITE Trip Rate})/(\text{Error} + 1)$$

Each issue and scenario is applied independently to the trip rate in Table 5-3 below to demonstrate the direct impact to each trip rate.

**Table 5-3 Case Study Estimates of Error and Adjusted Trip Rate for Convenience Market and Supermarket Land Uses**

	Method	Convenience Market (LUC 851)		Supermarket (LUC 850)	
		Error <sup>2</sup>	Adjusted Trip Rate <sup>3</sup>	Error <sup>2</sup>	Adjusted Trip Rate
ITE Trip Rate <sup>1</sup> [vehicle trips per 1,000 square feet]	ITE's <i>Handbook</i>		52.4		10.5
<b>Type of Error/Scenario</b>		<b>Error<sup>2</sup></b>	<b>Adjusted Trip Rate<sup>3</sup></b>	<b>Error<sup>2</sup></b>	<b>Adjusted Trip Rate</b>
Generic Land Use with Data < 10 Years Old <sup>4</sup>	Chapter 4	71%	30.6	74%	6.0
Peak-hour inflation <sup>5</sup> Built Environment	Chapter 3 Thesis <sup>6</sup>	20%	43.7	20%	8.8
Suburban		45%	36.3	45%	7.3
General Urban		100%	26.2	100%	5.2
Urban District		339%	11.9	339%	2.4
Demographics	Chapter 5				
High Income		35%	38.8	-38%	17.0
Low Income		-18%	64.0	38%	7.6

**Notes:**

<sup>1</sup> Average ITE Vehicle-trip rate for the Weekday, PM peak hour of the adjacent street traffic (4:00PM to 6:00PM) collected from ITE's 9<sup>th</sup> edition *Manual* (Institute of Transportation Engineers 2012). It is measured as vehicle trips per 1,000 square feet.

<sup>2</sup> Error is defined as  $Error = 100 * \frac{(ITE\ Estimate - Adjusted\ Estimate)}{Adjusted\ Estimate}$  [percent]. A positive value indicates ITE's rate overestimates, on average, for the given context.

<sup>3</sup> The adjusted trip rate is defined as  $Adjusted\ Trip\ Rate = (ITE\ Trip\ Rate) / (Error + 1)$ . Each adjusted rate is calculated for the specific scenario indicated in the left-hand column.

<sup>4</sup> The regressions examining the relationship between age and vehicle-trip rate were not developed for predictive purposes. Instead of estimating the correction for age directly, we apply the generalized land use rates developed in Chapter 4, Table 3-7, Model M2 (b). For convenience markets, C=1 and H=0. For supermarkets, both C and H =0.

<sup>5</sup> The peak-hour inflation ranged from 6% to 60%, with the average values between 20-25%. A conservative value is calculated here.

<sup>6</sup> The method used to estimate reductions in vehicle-trip rate for the built environment can be found in (Currans and Clifton 2015).

If we assume these errors are multiplicative—that one may apply the adjustments together, one after another—a cumulative adjusted rate can be estimated, accounting for all four potential biases identified (see Table 5-4). For both land uses, the compounding adjustment for all five contextual issues results in the vehicle-trip rates that are

significantly—and often severely—lower than ITE’s *Handbook* rates. Note that even in contexts where ITE’s data are recommended for application (suburban, middle income levels), ITE’s vehicle-trip rates still overestimate demand by 100% or more of the cumulatively adjusted trip rates (52.4 versus 17.6 and 10.5 versus 3.5 in Table 5-4) for both land uses. The supermarket scenarios are depicted further in Figure 5-5, where each adjustment is added in a cumulative manner (one after another).

**Table 5-4 Case Study Vehicle Trip Generation Rates Adjusted for Age, Peak-hour Inflation, Area Type, and Income**

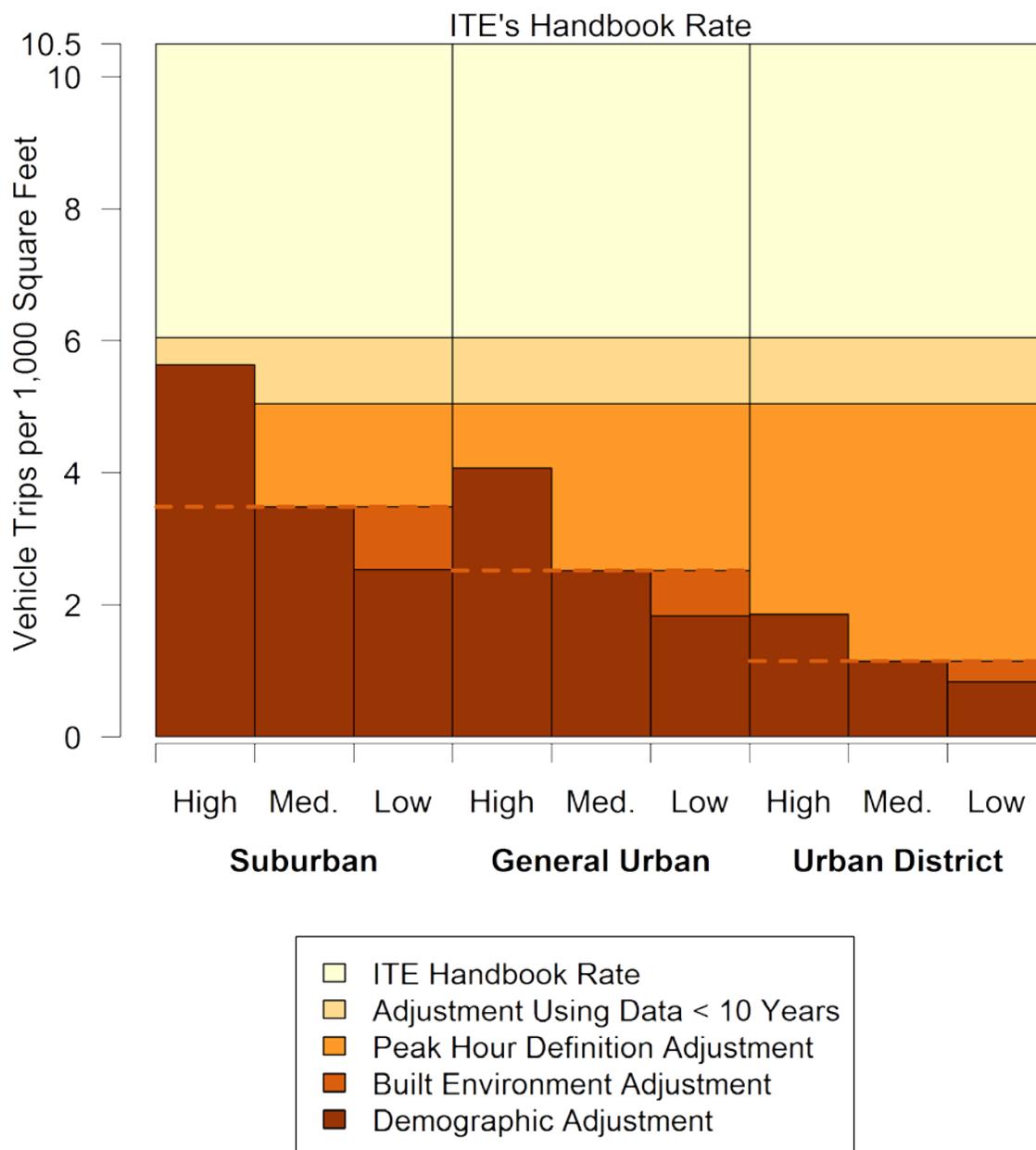
		Income		
Convenience Market (LUC 851) <sup>2</sup>		High	Middle	Low
Area	Suburban	13.1	17.6	21.5
Type <sup>1</sup>	General Urban	9.4	12.7	15.6
	Urban District	4.3	5.8	7.1
Supermarket (LUC 850) <sup>2</sup>		High	Middle	Low
Area	Suburban	5.6	3.5	2.5
Type <sup>1</sup>	General Urban	4.1	2.5	1.8
	Urban District	1.9	1.1	0.8

**Notes:**

Adjustments were applied in the following order: (a) Data < 10 years of age, (b) peak-hour inflation, (c) area type, (d) income level.

<sup>1</sup> Area type and income ranges are described in Table 5-2.

<sup>2</sup> Original vehicle trip generation rates from ITE’s *Manual* were 52.4 and 10.5 vehicle trips per 1,000 square feet for convenience markets (land use code, LUC, 851) and supermarkets (LUC 851), respectively.



**Figure 5-5 Case Study Vehicle Trip Generation Rates for Supermarkets - Adjusted Cumulatively for Age, Peak-hour Inflation, Area Type, and Income**

There are limitations to this application. Although the adjustments suggest convenience market vehicle-trip rates would increase for lower-income areas, it is more likely that overall person-trip activity increases, but automobile mode share estimates

decrease. The Chapter 4 estimate adjustment—an analysis of transaction counts—reflects variation in overall activity levels sensitive to area-wide income, but the mode share adjustment (Currans and Clifton 2015) is not sensitive to variations in income. When methods are not consistently sensitive to the same metrics of temporal, spatial, and social contexts—the multiplicative application of these adjustments may over correct for some scenarios and under correct for others. Overall, however, in most scenarios, ITE’s vehicle-trip rates inflate demand for vehicles—compounding error from misapplication in contexts not reflected by the original data.

### **Conclusions**

Perhaps the most alarming outcome of this study is the degree of inflation of vehicle trip generations for all scenarios. These data are widely used in agencies across the US and Canada in many aspects of the development review process: transportation impact analyses, impact fees, system development charges, utility fees, and estimating vehicle miles traveled estimation. For all of these uses, the overestimation of automobile impacts results in higher charges and more automobile mitigations. The propagation of these impacts, even in areas where the adjusted rates are closer to ITE’s rates, results in the pernicious over-supply of automobile facilities across cities of all sizes.

One possible outcome of the inflation of automobile demand may also influences the land development process itself. For new development, the estimation of vehicle trip generation is coupled with an analysis that evaluates adjacent facilities by a “level-of-service” metric that grades the impacts on an A through F scale using various performance metrics (vehicle delay, vehicle density, etc.). In already developed areas, the

level-of-service may already be nearing the agency regulated “failure” threshold. In growing economies, where developers find a need to build more densely—and the local zoning regulations support it—inflated automobile demand estimates push developers scale their development to lower densities to meet thresholds. Thus, the zoned future densities planned to meet the regional goals would be inhibited by the very tools used to estimate the demand to evaluate these goals.

Ideally, agencies will broaden the use of multiple alternative performance metrics—introducing each as a single piece of a larger puzzle for evaluating impacts of new development. In some cases, agencies are already aiming to do this—aligning and balancing the evaluation of development with regional and neighborhood goals and objectives, e.g., (City of Portland 2014; Kittelson and Associates 2014; Puget Sound Regional Council; City of Bellevue; King County Metro 2009). Concurrently, the *Highway Capacity Manual* (United States National Research Council 2010) now provides alternative and supplementary ways to evaluate the performance of non-automobile facilities. Researchers and practitioners have partnered with ITE to integrate new data, protocols, and tools to estimate multimodal demand (Bochner et al. 2016).

These new tools are used as a supplement to existing methods—adding the evaluation of bicycle level-of-stress alongside the evaluation of automobile level-of-service. However, if ITE’s original data, still a common mechanism for subsequent adjustment methods, is consistently predicting a “worst case” vehicle-trip rate, can we say any process that includes these data as one of several outcomes is a fair and balanced process?

More research is necessary to understand the range of impacts these methods have had, or will have, on land-use development. As urban agencies move toward more sustainable objectives and goals that incorporate multimodal planning, reducing dependence on gasoline, and increasing the accessibility (and densities), it is clear that the methods used to determine development-level impacts warrant another look. In the meantime, extrapolating ITE's data into contexts not originally controlled for may result in a self-fulfilling prophecy. Until we aim for where we want to go, we will struggle to achieve the future for which we planned.

## CHAPTER 6 CONCLUSIONS

This dissertation consisted of four papers, written as chapters. The first paper (Chapter 2) examined the issues and limitations of both innovative. Chapter 3 and Chapter 4 tested two assumptions commonly used in both the state-of-the-art and state-of-the-practice. Chapter 5 evaluated the conventional methods (ITE's *Handbook*) of urban trip generation for development-level evaluation of transportation impacts. Each of these chapters includes their own detailed conclusions. In this section, I discuss the findings more broadly, including implications for the development review process, recommendations for practice, study limitations and future work.

### **Implications for the Development Review Process**

In Chapter 5, I explore the potential extent compiled bias of these data, so commonly used in development-review processes, when the spatial, social, and temporal contexts of application are ignored. The bias, in many urban cases, is extensive—substantially overestimating demand, also known as “phantom trips” (Millard-Ball 2015), vehicle trips consistently estimated that never turn up. And since these data are used for some many different types of evaluation, the implication is that we are over-planning, over-charging, and over-mitigating for automobile demand at many retail and service land uses (and probably others as well).

When new (or rezoned) development is assessed for automobile demand in urban areas, there are two potential outcomes (not mutually exclusive of one another). First, developers may be required to mitigate for impacts that indicate the “failure” of facilities, where estimated demand exceeds capacity—adding capacity to adjacent roadways,

access, parking, or intersections. This increases the estimated capacity of facilities to accommodate these “phantom” trips. Second, developers may be charged for their impacts in the form of impact fees, system development charges, or utility fees. In the case of urban retail (specifically food retail, as studied in this manuscript), development evaluated using these inflated automobile data are required to pay more money into the system than they are generating. Of course, this depends on the assumption that development will always only be evaluated using an automobile-based metric.

Transitioning to a multimodal evaluation system may mean that development is required to pay for the pedestrian trips and bicycle trips generated—but the mitigations for this (particularly in urban areas) are likely less expensive than the costs of widening roadways or expanding intersections (especially with the costs of acquisitioning land). In some cases, this may reduce the amount of available land to develop for businesses or housing—requiring it to be used for additional automobile facilities (Manville 2017).

However, in times of growth where there is more economic demand for businesses and residential units, there may be a far more damaging limitation to misapplication of these data outside of their intended contexts. For developers aiming to maximize the value of their land, these data and corresponding transportation impact studies may be used as a means for scaling development—identifying early in the permitting process how large the development may be built without triggering extremely expensive automobile mitigations (e.g., road widening, adding signalized intersections, upgrading facilities already at capacity). In these situations, developers may build some fraction of their desired scale. Here, the misapplication of ITE’s *Handbook* data in urban

locations, ignoring potential variations in social or temporal contexts, may suppress development—reducing opportunities for density, decreasing the ability for developers to maximize the value of their land, and decreasing potential monetary exactions accrued from larger developments (e.g., additional apartments, more retail, more office space) for local agencies. These data—originally developed explicitly traffic engineering purposes—are then quashing development, constraining the ability for the land use to be fully maximized in accordance with zoning plans. While some have quantified the costs of overestimation in terms of requiring automobile mitigations, overcharging development, and overbuilding automobile facilities on potentially developable land—the extent of this suppression problem, a case of stated and revealed preference for development scale, is an area for future research.

Looking to the future, these findings may only worsen. These data are used to predict a future—estimating potential demand of land use. However, these data often do not reflect the changing landscape of transportation options, policy or land use. With the advent of autonomous vehicles, some agencies may set their sights on vehicle-based transportation charges—shifting from charging development for automobile demand, to charging the user directly. This may not remove the need for development-level review entirely—agencies may still wish to assess non-automobile demand and mitigations to meet their regional or neighborhood goals for health, safety, or accessibility, for example—but it could likely shift the focus of automobile-mitigations from a site-level evaluation to regional-level evaluation. Similarly, the way in which individuals interact with land use is also likely to shift. With the rise of online retailers and services, many

brick and mortar have been closing their doors, some opting for online versions of themselves entirely. And yet, data from mid- to late-century department stores, shopping centers, and big box retailers are continually applied for new retail—despite declining use.

The underlying problem of the reliance of these data is that they are often misapplied in contexts and applications for which they were not originally intended. They were developed for the purpose of evaluating adjacent automobile facilities, evaluating counts of vehicles through intersections—not for multimodal facilities, not for system development charges, not for estimates of vehicle miles travelled, not for scaling development, all of which are common uses of these data. Second, these data were never intended for urban applications—or even for suburban applications where there is desired non-automobile demand. Third, these old data are being used to predict the future, in a world where the way in travel is changing, and rapidly.

And yet, the continued reliance of these traffic data could be harming the very regional goals and plans agencies intend to achieve by overcharging development, overbuilding automobile facilities, and potentially suppressing economic development.

**So, where do we go from here?**

The underlying conclusion of this research is that ITE's *Handbook* data and methods are not suitable tools to evaluate sustainable, multimodal development.

Alternative approaches to development-level review require sensitivity of the travel outcomes to deliverable metrics identified in regional or neighborhood plans or goals (such as walkability, safe routes to schools, equitable access to affordable food, or

limiting emissions exposure to all facility users). These new methods should be developed under the guidance of multiple stakeholders, for example: policy makers, developers, transportation and land use planners, landscape architects, economist, academic researchers, travel behavior specialists, and traffic engineers. Given the numerous purposes for development-level review (e.g., assessing charges, evaluating adjacent facilities, examining emissions impacts, meeting regional or local goals, assessing equitable access), not every outcome (or scale of measurement) may be relevant for every type of review or assessment.

Furthermore, as rapidly as technology changes, behavior at and around different land uses and activities is also changing. The ability to evolve practice quickly, creating flexible tools that change as research and understanding change, will be necessary.

Beyond that, using older data collected prior to these numerous changes leads to issues when applying it in a predictive manner, particularly when those data are more than a decade (some half a century) older than the current development. How does using old data provide an adequate proportional nexus when planning for the future? Or rather when these old data—collected from unrepresentative suburban locations—conflict with more comprehensive regional plans (e.g., transportation system plans, comprehensive plans, each developed with substantial public insight), how might agencies use alternative data and methods to more broadly understand the range of impacts and corresponding trade-offs to make a decision that more adequately assesses the situation? This would likely depend on a number of travel outcomes and policy variables, more than a constant

“vehicle trips per square footage” rate applied for all flavors of development in all contexts.

Considering all the issues described and discussed throughout this text, there are many reasons to be concerned about the use of these data—or perhaps this approach more broadly—for assessing the impacts of development on the transportation network. This begs the question, is this approach the best way to assess impacts? Or rather, are there better ways to get at the same result: estimating a proportionate nexus to share the burden of developing, operating, and maintaining the transportation system across users? Shifting practice’s thinking from the current framework for estimating demand, there are many ways this approach could begin to vary: moving from a development-level assessment to an individual trip-maker-level; shifting from automobile trips to overall activity (transactions, sales, person trips); changing the site-level scopes to something on the neighborhood scale; or broadening evaluation from a single transportation metric to multiple metrics. Given the likely technological changes on the horizon, acceptance of a more flexible or dynamic framework—perhaps taking advantage of ongoing data collection through big data sets or the willingness to accept multiple types of data or approaches—or of the inherent uncertainty in predicting the future demand would be useful as well. Alternatively, the current approach may be more attractive to existing users. However, given the findings from this research, continued use of this method and data will require significant investment (e.g., money, time, research) from stakeholders, including agencies, practitioners, developers, and ITE themselves.

## **Recommendations for Practice**

In the near term, there are several things agencies, ITE members, and practitioners (both planners and engineers) can do to make direct improvements to this process.

### ***Agencies***

Presentations and studies on innovations in trip generation are often written for the practitioner, but agencies have perhaps more autonomy in moving the state-of-the-practice than any other stake holder. Agencies that require alternative data sources and methods with sensitivity to local contexts recognize the limitations of ITE's data and take steps to correct them.

A pooled fund study may be useful for agencies with fewer resources (including transportation engineering staff) to commit to testing, validating, and incorporating innovative data and methods into transportation impact review guidelines, and negotiating alternative rates. If half of the metropolitan organizations in the US (just over 200 agencies) donate an average of \$4,000 per year, 100 new multimodal person-trip counts could be collected annually. Pooled studies mean the data collection could incorporate strategic sampling (instead of convenience sampling), specific research questions could be addressed, and more comprehensive guidelines for accommodating local contexts could be incorporated.

The reliance on a single metric for any type of evaluation means that any bias associated with that data—whether recognized or not—is introduced into the review process. Similarly, agencies should consider incorporating multiple alternative metrics. In the case of development-level evaluations, there is substantial evidence (in this

dissertation as well as the work of others) that the bias has led to the overdevelopment of automobile facilities, often inhibiting regional plans that call for more multimodal and livable goals. Agencies in California are certainly leading the way; shifting the focus of site-level review to vehicle miles traveled, but also opening the process up for incorporating metrics such as mode share. A shift away from an overwhelming reliance of ITE's data also opens the door for improving the connectivity between regional transportation plan—with multiple goals and objectives—and site-level development. In the end, connecting these processes will encourage development to meet the needs of the community for which agencies represent.

But these changes require more than just input from agencies.

### *Institute of Transportation Engineers*

The development of ITE's data has been a silo-ed process in the past. As a professional organization serving transportation engineers, the majority of the people at the table influencing these methods have been practicing traffic or transportation engineers. By reaching out to agencies and across disciplines to improve this practice, ITE could increase the applicability of their data to reach broader contexts. Continuing to balance committees and panels with representation from a diverse and balanced group of agencies—including engineers, planners, economists, developers, landscape architects, computer scientists—could speed up the process of improving practice, accommodating new issues identified, and innovating solutions. This may be the only way to incorporate and accommodate the numerous transformative technologies being developed.

One of the strongest recommendations ITE can make is to remove older data from active use. While there is not enough information to understand *why* vehicle-trip rates have changed over time, the limited contextual information provided for these data prevent a thorough understanding of ITE's contexts. Decommissioning older data would remove approximately 95% of the existing *Handbook* from active use, spurring the demand for newer data.

And with a growing demand for new data, ITE should consider broadening the types of data beyond multimodal person trip information—including information about trip length or vehicle miles traveled, parking and pricing information (a currently disconnected practice), and less considered metrics (travel time, comfort, economic expenditures). This may correspond with a more open approach to innovative techniques for capturing this information and reconciling it with existing metrics—like providing guidance for alternative data collection techniques, such as transaction counts or “big data”. ITE recommendations are often the only option for practitioners working in jurisdictions with few resources. Opening the scope of these data would provide more flexibility for agencies and practitioners to accommodate their own local contexts and goals.

### ***Practitioners***

The most important things practitioners can do to improve the state-of-the-practice is to practice good professional judgment by advocating for contexts-sensitive methods and data and to find opportunities in share experiences and case studies so that others may to do the same.

## **Study Limitations & Future Work**

The specific limitations of each paper were discussed in the corresponding discussion and conclusions sections of each chapter. In this section, the broader limitations of this sort of research is explored, along with potential future work to build on this study.

One of the most prevalent issues encountered in this research was related to the lack of transparency in ITE's data discussed in Chapter 3, but also in Chapter 2 and Chapter 5. The lack of information associated with these data results in the inability to understand the contexts of ITE's data. While ITE recognizes that good professional judgement requires the user to understand the "derivation and initial context" of data and methods before applying them, they do not provide adequate information to fully understand where and when their data should be used. Added transparency (e.g. location information, description of environs) is one way to improve the use of these data.

Evaluating the costs and benefits of decision would be another improvement. In Chapter 3, the results indicated an aggregated land-use taxonomy for retail and services (three categories) performed nearly as well as ITE's more extensive taxonomy (32 categories). Aggregating uses along these lines also provides a larger sample within each category—increasing the ability to control for contextual variables identified as important (temporal, spatial, social).

One observation made while reviewing transportation impact studies from practice was the potential for prematurely scaling development by using inflated vehicular estimates in inappropriate contexts. This is particularly problematic where (a)

developers want to maximize density, (b) where zoning allows for higher densities (urban areas), and (a) the study area includes facilities nearing the ‘failure’ threshold. In these areas, using ‘off-the-shelf’ methods that overestimate demand means that everyone loses: the developer is not able to maximize their investment; the agency is not able to capitalize on the development by increasing density and capturing additional development charges; and the public has to adapt to an oversupply of automobile facilities and an undersupply of housing, work-space, and other destinations.

Even with more robust methods, there still exists a fair amount of uncertainty in these data and methods—demonstrated in Chapter 4 the bootstrapped confidence interval was calculated to demonstrate the distribution of potential demand estimated. And yet, average trip rates often determine the recommendation for mitigations offered, with little to no reflection on whether the network improvement reflects broader regional goals or objectives (let alone if these “average” rates are biased). Perhaps a more adept approach to handling the limitations of these data would be to add additional performance measures that balance the flaws of ITE’s data with alternative metrics for evaluating demand and impacts. In this situation, ITE’s data would provide one piece of the TIS puzzle, and other impact outcomes could be considered in this process. This may open the door for alternative data collection technologies—such as the transaction counts analyzed in Chapter 4.

A broader approach to evaluating development may also support the changing landscape of transformative technologies: autonomous and connected vehicles, information and communications, shifting distribution and warehousing mechanisms

changing the face of retail. If we can only guess at what the future holds, then perhaps relying on 50-year-old data may not be the best way to predict the future (Figure 5-1).

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## APPENDIX. COMPARING TRANSACTIONS AND TRIPS

To compare the fundamental difference between transaction counts—a measure of economic activity—and person-trip counts—a measure of behavioral activity, we explore the characteristics of a trip that links these two data together. Although the author does not have access to transaction and trip counts observed over the same time span, this analysis considers the aspects that link transportation activity to economic activity. To begin, we identify the following variables:

$l = \textit{location of establishment}, l \in \{l, L\}$

$i = \textit{hour of observation}, i \in \{i, I\}$

$c = \textit{customer group represented by each transaction}, c \in \{1, C\}$

The sum of customer groups,  $c$ , for any given hour,  $i$ , and location,  $l$ , sums to the total number of transactions for the given hour and location, such that:

$T_{il} = \textit{Transactions observed for hour } i \textit{ at location } l$

Each transaction is treated as an indicator of groups moving to and from the site. When using transactions to represent activity at locations, one must consider how participation for the activity, in this case grocery shopping, occurs. Specifically, we are investigating the assumption that group size does not vary by location indicators used in the transaction analysis, nor would it vary by time of day or day of week. To test this, we consider a 2011-2012 household travel survey (HTS) collected in Portland, Oregon, the same area that the transaction data were collected. We test this assumption using a subset of the survey, examining only those activities conducted during “routine shopping

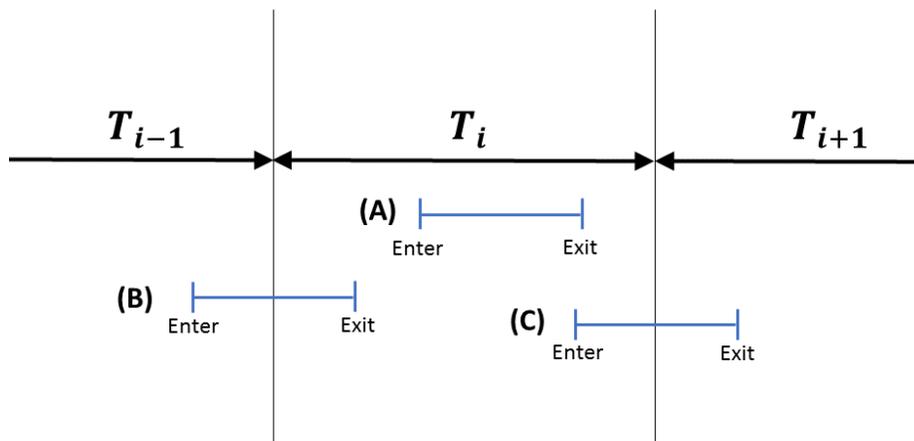
(groceries, clothing, convenience store, household maintenance).” For site-level evaluations, there are limitations when using household travel survey data, particularly when attempting to connect activities recorded on the survey—explained based on trip purpose—and activities occurring at specific land uses—defined by the product or scale of the establishment. This is discussed later on in this examination.

Since HTS data are collected at an individual household member level, there will exist multiple records for each unique group trip, each one for a different family member. Although HTS collect data for every member of the household, it also records how large the “group size” of each activity was so that one can determine if there were non-household members participating in the activity. Aggregating the data so that each observation in the data set represents one group trip to the “routine shopping place” recorded is the first step to accomplish this. The location of the place is then geocoded and mapped to obtain commiserate values for each of the three location variables: regional accessibility, local accessibility, and area-wide median income. The time and day of the start of the activity (the entrance) and the end (the exit) were also recorded.

To evaluate assumptions about groups size, the group size was regressed upon all three location variables as well as dummy variables for time of day and day of week using a negative binomial regression, which considers the count-based values of the independent variable. None of the coefficients estimated significantly contributed to the explanation of variance in group size; only the intercept constant,  $G$ , was significant. Thus, the assumption holds that group size of visitors observed at routine shopping establishments does not vary by location or time, and, therefore, remains constant:

$$G = 1.52 \text{ people per visit}$$

When relating transactions to person trips is contemplated, one must consider the relationship between the transaction itself and the times at which the participant arrived and left the site. We assume that a person exiting directly after a transaction in an hour,  $i$ , entered during the same hour only a little while earlier. But trips to the store are not planned on an hourly basis, and, therefore, some overlap between transactions in one hour, and entering trips in the hour before is likely (see Figure A-1). Here, we not only assume that the time period of transaction  $T_{it}$  for any given customer is the same time period that the group exited the establishment, but also that we recognize that exiting after a transaction occurs likely takes a few extra minutes.



**Figure A-1 Examples of Three Visitor Groups who: (A) complete their activity within the same hour,  $T_i$ ; (B) exit during the given hour, but enter during the hour previous, and; (C) enter during the given hour, but exit during the hour following**

To examine the relationship between the probability that customers arrive and leave within the same hour as the transaction, we create a binary variable that identifies any group that recorded arrive and departing the activity within the same hour of the day. This takes into account both variation in the duration of the routine shopping activity, as

well as the arrival patterns of the groups, while making the interpretation comparable to transaction totals aggregated to the hour. We then regress this binary variable on location (regional and location accessibility and area-wide median income) and temporal variables (hour of the day and day of week) using a binary logistic model. The outcome or dependent variable being predicted can be expressed as the following:

$$P_{li} = \textit{Probability that customer group enters the same hour that they exited}$$

Similarly, it will be necessary to know the overlap of transactions (or departures) that occur during a different hour than the entrances, which can be described as follows:

$$1 - P_{li} = \textit{Probability that customer group did not enter and exit the same hour}$$

With the same sample of 3,144 trips stops for “routine shopping (groceries, clothing, convenience store, and household maintenance),” the following model is constructed, representing only the significant coefficients estimated for two indicators: location accessibility (ACTDEN) and area-wide median income (INCOME10k, in \$10,000 annual dollars).

$$P_l = \frac{1}{1 + \exp(-(-0.28 + 0.53 * ACTDEN + 0.043 * INCOME10k))}$$

These results suggest that the probability that customers came and went during the same hour—which relates to both the arrival patterns of survey respondents as well as the duration of the visits—did not have statistically significant relationships between the regional accessibility nor any of the temporal variables. The results did indicate a significant relationship with local accessibility and income, however, suggesting that as either of those variables increases, so does the probability that customers will enter and

exit during the same hour. This analysis is not robust enough to provide a direct or conclusive idea as to why these indicators were significant, but similar significance and relationships were found when regressing the duration of the visit upon the same variables. This may suggest a relationship between shorter durations (and a higher probability that visits can be made within the hour) for areas with higher local accessibility and area-wide median incomes. Since the results suggest that this probability does not change over time, a given establishment will have one probability value,  $P_l$ , calculated based on the location properties,  $l$ , of that establishment.

To put this all together, we consider Figure A-1 above. The person trips,  $PT_{li}$ , for location,  $l$ , and hour,  $i$ , can be calculated for the number of group trips occurring during every hour multiplied by the average group size. The number of group trips can be calculated from summing up: (A) all the group trips that arrive and depart within the same hour,  $GT_{2way}$ ; (B) the group trips that exit during the given hour (but enter in the hour previous),  $GT_{exitonly}$ , and; (C) the group trips that enter during the given hour (but exit during the following hour). For (A), we count all trips that likely occur within the hour,  $P_l$ , as two directions. For (B) and (C), we count only the one direction that occurs during the hour,  $(1 - P_l)$ . For (B), we include only the exit of the transactions that occurred during the given hour, but for (C), we include only the entrance trips that exited during the hour following,  $i+1$ .

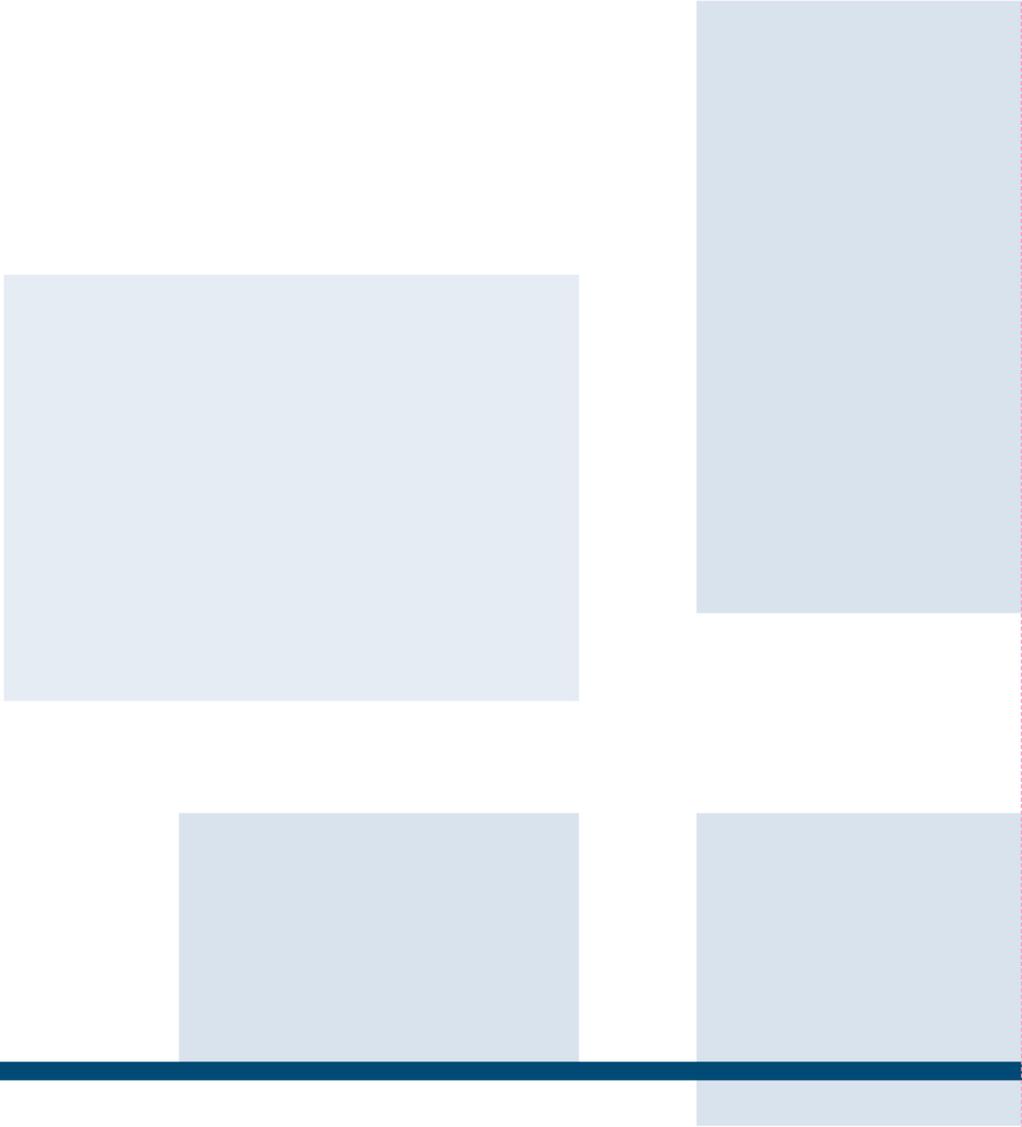
$$PT_{li} = G[GT_{2way} + GT_{exitonly} + GT_{enteronly}]$$

Where,

$$GT_{2way} = T_{il} * 2 \text{ direction} * P_l$$

$$GT_{exitonly} = T_{il} * 1 \text{ direction} * (1 - P_l)$$

$$GT_{enteronly} = T_{i+1,l} * 1 \text{ direction} * (1 - P_l).$$



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